BRAIN TUMOR DETECTION AND CLASSIFICATION USING DEEP LEARNING FROM MAGNETIC RESONANCE IMAGES

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APPROVAL

This Project titled **"Brain Tumor Detection and Classification Using Deep Learning From Magnetic Resonance Images"**, submitted by Shourav Molla, ID No: 191-15-2438 and Md. Ali Azam, ID No: 191-15-2417 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfilment 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 January 2023.

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We hereby declare that, this project has been done by us under the supervision of **Taslima Ferdaus Shuva, Assistant Professor, 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

Brain tumors are the most conventional and aggressive illness and have an extremely low life expectancy in its most severe form. Uncontrolled growth as well as proliferation of skull cells results in the formation of brain tumors. Given the difficulties of tumor biopsies, deep learning-based brain tumor analysis frequently makes use of three dimensional (3D) magnetic resonance imaging (MRI). In this article, a detailed analysis of different deep learning method is presented for the classification of multiclass brain tumor which may increase the level as well as efficiency of MRI engines in detecting the disease. Before using the image dataset to stabilize the output of four previously trained convolutional neural network (CNN) models, it undergoes a variety of data pre-processing techniques. The pre-trained prototypes used in this study are EfficientNet, Xception, MobileNet, and ResNet-50. Accuracy is shown to rise as the period progresses where the highest accuracy of EfficientNet, Xception, and MobileNet is 98.18%, 97.23%, and 96.96%, respectively where ResNet-50 comes with a moderately much lower accuracy score of 95.66%. The supremacy of EfficientNet over all other models is discovered in Precision, Recall as well as F1-Score while classifying brain tumor cells.
Keywords*:* Machine Learning, CNN, Brain Tumor, Health Care.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

Brain Tumor, also referred to as an intracranial neoplasm, is an abnormal lump of tissue where cells develop and reproduce out of control while appearing to be normal by the human body mechanisms that regulate healthy cells. Among all types of diseases, the brain tumor is considered to be the most dangerous as it may lead to a high rate of mortality and even the root cause of this disease is still unknown. In this regard, a brain tumor can eventually turn into a cancer. According to the American Brain Tumor organization report, in 2021 the primary malignant brain tumors were found in more than 84,000 patients that caused the deaths of around 18,000 individuals [1]. But if the tumor can be identified at an early stage the survival rate can be maximized to a great extent. Generally, tumors inside a human body are classified based on two things: i) whether the cells are cancerous or not, ii) the originating place of these cells. In this regard, Benign refers to a condition where the growth is not cancerous and does not spread and invade nearby tissues very fast suggesting to the fact that it is not serious. On the other hand, Malignant cells are cancerous and tend to have rapid growth. During the last stages of these cells, they are resistant to treatment and even can recur after all traces have been fully destroyed. Presently, there are more than 150 different categories of brain tumors that have been acknowledged around the world leading to two major groups which is Primary as well as Metastatic [2]. The primary brain tumors initiates from the inside and immediate environments of the brain and tend to stay there. The most typical types of primary brain tumors include glioma, meningioma, and pituitary tumor [3]. A typical form of tumor with brain origins is the glioma also called as intra-axial brain tumors. Gliomas, which include astrocytes, oligodendrocytes, and ependymal cells that surround as well as support neurons in the brain, justification for around 33% of all brain cancers. Meningioma tumors grow slowly mostly in membrane that surrounds the brain and spinal canal. Usually, these tumors can contain non-cancerous cells and are extremely unlikely to expand. Later, a pituitary tumor occurs in the pituitary gland, and regulates the activity of other tissues and regulates the balance of hormones in the body [4].

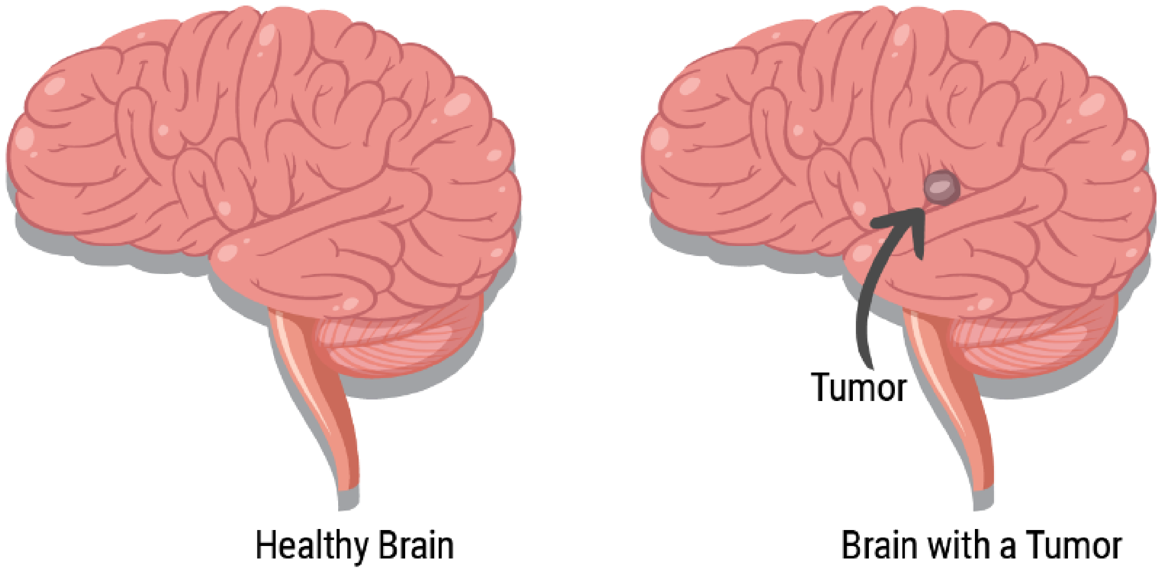


Figure 1: Healthy brain vs Brain with a tumor.

The recognition of brain tumors is a struggling piece of work due to the heterogeneous nature of the tumor cells. These types of tumors are often diagnosed using two approaches such as direct brain biopsies as well as neuroimaging. Presently, systems using computer-aided analysis have been promoted as a helping tool to detect brain tumors where MRI (Magnetic Resonance Imaging) is ideally considered as a best method as it is non-invasive and offers superior resolution for soft tissues compared to other types of medical imaging techniques [5]. In such systems, feature extraction from previously processed MRI images, feature reduction, and ultimately classification consuming a supervised learning algorithm are the crucial steps for disease detection.

1.2 Motivation

A non-invasive technique for creating three-dimensional (3D) tomographic pictures of the human body is magnetic resonance imaging (MRI). The most frequent application of MRI is to find cancers, lesions, as well as other anomalies in soft nerves, such the brain. In clinical settings, radiologists qualitatively examine MRI scanner film. Magnetic resonance (MR) image analysis and visualization methods with computer assistance have recently been studied. On identifying and measuring brain anomalies, several studies have concentrated. An essential element in this procedure is automatically locating the brain in head MR images. Data quality assurance is a crucial stage in the computer-aided analysis process. Due to flaws in MRI scanners, MR pictures include undesired intensity imbalance. The accuracy of computerized analysis can be increased by eliminating or minimizing These variances. An innovative, totally automated technique for intracranial border identification and intensity correction in head MRI images is presented in this thesis. The line separating the brain from the cerebral cavity is known as the intracranial border. It distinguishes the brain clearly from other head characteristics.

1.3 Rationale of the Study

Numerous automated systems have been investigated for the aim of tumor detection, some of which are discussed below in the 2018 discussion of the proposed work by Remy Y. and Verset L., who categorized high grade gilomas. The giloma that most usually affects both adults and children is astrocytoma. Different types of astocytes are seen in both low grade and high grade gliomas [6].

This work's CNN was entirely automated. Python was used to implement CNN in the system. The concept of AI was implemented using the Anaconda framework, which creates the BRATS database utilizing Tansorflow and neural organization network. Improved segmentation accuracy and the availability of features to process larger datasets2015 saw the competitive analysis of MRI image brain tumor findings using images from the BRATS collection. The disc of coefficient is a parameter that used describe the accuracy of automatic segmentation [7]. The MRI test frequently generates a ton of data, which makes manually comparing tumors to non-tumors quite time demanding. Even if it only offers accurate quantities measurements for a small number of photos. As a result, a reliable automated classification approach is now required to reduce the rate of human fatalities. Because of the enormous anatomical and spatial heterogeneity of the surrounding brain tumor-bearing regions, the automatic identification of brain tumors is frequently quite challenging. As a result, a deep learning-based program was developed to identify cerebrum tumors [8]. Mzoughi et al. [9] recommended using a pre-processing strategy focusing on sensitivity standardization and adjustable contrast improvement to develop a fully automated 3D CNN framework. They used the Brats-2018 dataset to reach an overall accuracy. With the aid of a convolutional neural network (CNN), local interpretable model agnostic explanation (LIME), and Shapley additive explanation (SHAP)

1.4 Research Questions

1. What is Brain Tumor status globally?
2. What are the associated factors with brain tumor?
3. Which algorithm perform well and why?
4. What is image processing?
5. How does EfficientNet Model, Xception Model, MobileNet Model, ResNet-50 Model?

1.5 Research Objectives

1. To find out the Brain tumor status.
2. To find out the supplementary factors.

3. Finding the best performing algorithm.
4. Making Consciousness to decrease the percentage of Brain Tumor in every year.
5. Giving massage with the influence of missing knowledge on Brain Tumor causes to peoples.
6. To increase the knowledge on Brain Tumor preventing factors.

1.6 Report Layout

1. In the first chapter we discuss about the motivation relational study and objectives.
2. In the second chapter we discuss about the associated word and Research summary.
3. Research methodology data collection and the pareshan research subject and instrumentation and discuss about the applied model in the chapter 3.
4. The experimental evaluation and the numerical results of the study are discussed in chapter 4.
5. The fifth chapter discussed about Impact on Society and environment and sustainability.
6. Conclusion, recommendation and implication for future research has been discussed in the sixth chapter.

CHAPTER 2
BACKGROUND STUDY

2.1 Terminologies

In this article we have used some of the terms:

1. **Brain Tumor:** An accumulation or rapid spread of abnormalities cells in the brain or its adjoining areas.

2. **MRI (Magnetic Resonance Imaging):** A medical imaging procedure that creates precise pictures of the inside anatomy of the body using a magnetic field as well as radio waves.

3. **Deep Learning:** An approach to machine learning that builds multi-layered artificial neural networks to understand from data as well as make predictions.

4. **Data Augmentation:** A method for artificially increasing the number of training data by subjecting the current data to random alterations.

5. **Computer-Aided Design (CAD):** A system that uses computer algorithms to assist in the diagnosis of medical conditions.

6. **Classification:** Classification is a type of supervised learning in which you instruct the computer to carry out a task using information that has already been annotated by people. For the computer to learn from, this training set has a predetermined number of labels or categories.

2.2 Related Works

A critical step in choosing the best treatment option is medical image segmentation, which uses magnetic resonance (MR) scans to identify and categorize brain tumors. There are numerous methods that have been suggested for classifying brain tumors in MRI. Sharif et al. [10] presented an approach for reducing the inspection process of brain tumors, as well as feature extraction was the key purpose of this work. The key-point method of contrast enhancement is originally used for tumor categorization. Following that, PSO is used to extract and optimize deep learning properties. The BRATS2017 and BRATS2018 datasets were used. While the accuracy of the BRATS2018 dataset is reportedly 88.34% for the central tumor, 91.2% for the complete tumor, and 81.84% for the enhanced tumor, the performance of the BRATS2017 dataset is projected to be 83.73% for the core tumor, 93.7% for the entire tumor, also 79.94% for the enhanced tumor (enhanced tumor). Additionally, a 92% accuracy level was observed when the classification approach was applied to the BRATS2013, BRATS2014, BRATS2017, and BRATS 2018 datasets. Narmatha et al. [11] provided methodologies for segmentation and classification using a fuzzy brain-storm optimization technique. In this way, the storm optimization gives the highest significance to the target constellation in the brain. The fuzzy procedure is applied several times in order to obtain the optimal outcome. With a projected accuracy of 93.85%, the experimental method used the BRATS2018 dataset. Sumaiya Pandey et at. [12] Al presented the technique of CNN to detect the presence of tumor. The first and only pre-trained model utilized in this study is VGG16 with extra dropout, flatten, dense layers, and sigmoid activation function, which produced an accuracy of 92% for the validation set as well as 80% for the experiment set. Banerjee et al. [13] highlighted about using a series of different MRI pictures to improve MRI image categorization using a convolutional neural network. The research made use of pre-existing models, like ConvNets and VGGNet, which were developed for interpreting different MRI images. When tested on various MRI datasets, the study estimated the effectiveness of the suggested models and reported that they were 97% accurate. Sajjad et al. [14] recommended a data augmentation technique CNN for brain tumor classification. The process of classifying brain cancers by means of segmented MRI images. They utilized pre-trained VGG-19 Deep convolutional neural network to classify the data, as well as the accuracy results for augmented and unaugment data, respectively, were 87.39% and 90.66%. Sultan et al. [15] used a CNN structure with 16 convolution layers, normalization and pooling, as well as a divide before the fully attached level. They found that using 68 percent of the photographs for training and the other images for validation and testing resulted in a 96 percent accuracy rate. The authors in [16] Deep convolutional neural networks have been studied by a potential tool for analyzing brain images. This article just skims the surface of deep convolutional neural networks. This study does not address the issue of the viability of segmentation in multi-modal learning under imbalanced conditions. ML techniques, which are a part of AI, are currently widely used in bioinformatics. The main kinds of this are monitored and unsupervised. The source to output mapping is carried out utilizing various mapping algorithms in supervised strategy instruction to anticipate unexpected data. Utilizing machine learning (ML) techniques like K-Nearest Neighbors Algorithm (KNNA), Support Vector Machine Algorithm (SVMA), and Artificial Neural Network Algorithm, the goal is to learn inherent connections within the data for training purposes (ANNA)[17][18]. Afshar et al. [19], it regulates the coarse tumor, confined to the BT categorization, as well as the MRI of the brain. This study yielded precision data at 90.89%. Three glioma grades have been classified with a precision rate of 90.9% (for the first analysis). A 94.2% accuracy rate for the classification of pituitary, meningioma, and glioma tumors was obtained by the subsequent contextual investigation. Unsupervised learning techniques, such the Self Organization-Map Algorithm (SOMA) and fuzzy-c-mean algorithm, on the other hand, simply employ the input parameters. It's important to extract the texture and grayscale characteristics from training photos, which may need segmenting tumors first. Progressive component learning and information portrayal are the foundations on which DLA builds AI-focused models and frameworks. DLA employs numerous nonlinear layers of handling for feature abstraction. The result of each successful layer is what the subsequent one contributes as we go further into the network. It also aids in the abstraction of data. CNNA is a subclass of DLA that is frequently used for visual imaging analysis as well. It is designed to require minimal pre-processing [20].

2.3 Comparative Analysis and Summary

There is a large amount of data available in the healthcare sector. With the right use of dependable data mining classifying methodology, early disease prediction is achievable. The fields of medicine have legitimately benefited from machine learning. The enormous importance if it is implemented properly. The study examines a set of risk factors that are monitored by systems for detecting brain tumors. It becomes crucial to find the tumor early in order to preserve lives. In this article, we will examine a comparison with related brain tumor detection models that provide us with our designed framework and demonstrate its excellent performance. Which is given in the Table 1.

TABLE 1: COMPARISON WITH RELATED BRAIN TUMOR DETECTION MODEL

Sudies	**Datsets**	**Models**	**Accuracy (%)**
Anaraki et al.[21]	TCGA-LGG MRI image dataset	GA	90.90%
		CNN	94.20%
Shelatkar,Tejas et al.[22]	RSNA-MICCAI dataset	YOLOv5	88.8%
Ait Amou, Mohamed et al.[23]	Figshare MRI dataset	VGG16	97.08%
		VGG19	96.43%
		ResNet50	89.29%
		InceptionV3	92.86%
		DenseNet201	94.81%
Kang, Jaeyong, et al.[24]	Three brain MRI dataset	ResNeXt-50	94.12%
		InceptionV3	92.16%
		DenseNet2	96.08%
Filatov, Dmytro et al.[25]	Br35H image dataset	EfficientNetB7	88.18%
		EfficientNetv2B1	89.17%
		EfficientNetB1	89.55%
		ResNet-50	79.32%
The approaches used in this research	SARTAJ Brain MRI dataset from Kaggle	EfficientNet	98.18%
		Xception	97.23%
		MobileNet	96.96%
		ResNet-50	95.66%

In clinics, a variety of procedures are employed to treat brain tumors. To reach this level of precision, automated or semi-automatic processes were needed. In accordance with study, segmentation and classification can be carried outautomatically by use of a technique that utilizes CNN and a tiny kernel. All the images in the dataset that we used are reshaped to 150X150 pixels because all image data are not in same size.

The image dataset Passes through a number of data preprocessing procedures before being used to stabilize the output of four previously trained convolutional neural network (CNN) models. Pre-trained prototypes EfficientNetB0, Xception, MobileNet, and ResNet-50 were employed in the study. The approach utilized in this study involves preprocessing, which involves removing noisy data from the data gathered during data collection. Following is the average filtering. For pixels-based identification, the classification method is used after. Python is preferred as the language of choice. For several factors, this was an easy call. A sizable community supports the Python programming language. It has a large number of potent tools ready for numerical computation. Packages like NumPy, Pandas, and SciPy are extensively documented, free, and available. It is possible to create and share information with live code, formulas, visualizations, and narrative text using the accessible Jupyter Notebook web application. It is used to implement Python code. According to the brain tumor classification method established on deep learning, the job is divided into two stages: training as well as testing. During the training stage, pre-processing, feature extraction, as well as classification consuming the Loss function are carried out in order to develop a classification model. This article explores, evaluates, and discusses how convolutional neural network (CNN) and magnetic resonance imaging (MRI) models are used to detect several forms of brain malignancies (including gliomas, meningiomas, and pituitary tumors) without the need for human interaction. Recently, techniques for computer-aided analysis have been marketed as a tool to help with magnetic resonance imaging (MRI) brain tumor detection (MRI). Due to its non-invasive nature, MRI is currently the best tool for the early detection of human brain cancers. A simple CAD system consists of several essential stages, including feature extraction from previously processed MRI images, feature reduction, and furthermore, categorization by supervised learning. The initial MRI scans are enhanced during the preprocessing step, where work on things like noise reduction and contrast augmentation is done. Brain tumor identification is being done with the use of deep learning. Finding the tumor on the brain imaging is difficult.

2.4 Scope of the Problem:

The scope of the problem of brain tumor classification and detection from MRI images using deep learning models can be defined as follows:

1. To look into the state-of-the-art for MRI image-based brain tumor classification and detection using deep learning.
2. In order to examine and address issues including the scarcity of increased, labelled brain tumor MRI imaging data, the wide range of appearances of brain tumors, and the difficulty of correctly differentiating between various types of brain tumors and
3. Categories of malignancy based solely on MRI images.
4. Identifying and classifying brain tumors from MRI images using revolutionary deep learning architectures and techniques that address these difficulties.
5. To research the application of transfer learning, data augmentation, as well as other strategies to enhance the appearance of deep learning models on MRI scans.
6. To assess the effectiveness and reliability of the suggested models using a sizable and varied dataset of MRI images.
7. To look into the interpretability as well as explainability using deep learning models, as well as the connection between some of the features that the models have learnt and the radiologists' diagnoses.
8. To determine whether it is feasible to use the suggested models in a clinical setting, taking into account the computing needs and compatibility with the infrastructure and workflows already in place.
9. To make suggestions for new lines of inquiry in the categorization and detection of brain tumors from MRI images employing models of deep learning.

2.5 Challenges

Deep learning to demonstrate there are several challenges associated with a brain tumor, along with the following:

1. Only a small amount of high-quality, labeled brain tumor MRI imaging data exists for deep learning model training and evaluation.
2. There is a lot of variation in the way brain tumors look between people and between MRI sequences and parameters.
3. It can be challenging to reliably differentiate between various grades of malignancy and various forms of brain tumors (such as gliomas, meningiomas, etc.) based solely on MRI imaging.
4. There is a need for reliable and effective ways for dealing with big and complex medical imagery data, particularly MRI data.
5. Deep learning models must be interpretable for clinical decision-making, especially when used with MRI images, which seem to be extremely complex and heterogeneous.
6. The necessity for the approaches to be reliable and generally applicable to MRI imaging data from various scanners and facilities that have not yet been examined.
7. The models must be computationally effective in order to be used in a clinical environment, particularly for large-sized MRI images.
8. To verify the models' clinical value and generalizability, they must be verified on a sizable, heterogeneous patient group.
9. The models must be easily adoptable in the clinical setting and connected with current clinical workflows and infrastructure, particularly for MRI images, which are frequently employed there.
10. The models' performance must be continuously improved over time by adding fresh MRI imaging data and clinical annotations.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

Early identification of brain tumors is a critical topic being researched by researchers due to its possibility of improving the rate of identification, medication, and rehabilitation for those affected. This sort of tumor may be detected using a variety of techniques, each of which has benefits and drawbacks. The technique in use uses mri image data from epidermal cells to identify and categorize brain tumors. A number of pre-trained models, including EfficientNet, Xception, MobileNet, and ResNet-50, were used to achieve the goal.

3.2 Data Collection Procedure

The dataset was obtained via Kaggle. Kaggle is the location in which data scientists invest their evenings and weekends. It is a crowdsourcing platform that attracts, teaches, educates, and tests a number of data scientists around the world to answer issues utilizing predictive analytics, machine learning, and data seience. It has over 536000 active members, and each month it receives roughly 150000 entries. It was started in Australia's Melbourne. Kaggle's initial investors in 2011 Silicon Valley included Max Levchin, Paypal, Index, Hal Varian, Google's Chief Economists, and Khosla Ventures. Together, they helped Kaggle raise around $11 million. In the end, Google bought Kaggle in March 2017. On Kaggle, data scientists from all around the world compete for prizes and to climb the rankings. As of right now, 94 persons are still kaggle Grandmasters. In every field of employment, data always comes before anything else [26]. We required the datasets to finish this deep learning process, so we downloaded them from the Kaggle website. Finding the ideal datasets for our needs was the biggest challenge using Kaggle, a massive data warehouse. As a result, we carefully examined the website and other references that we had read for our research summary. The dataset which is performed in the study was gained from the Kaggle repository that contains 3290 T1-weighted enhanced MRI images [27]. For training the model there were 2870 MRI images (Meningioma: 944, Glioma: 933, Pituitary: 507, No Tumor: 906) and the rest 420 images was used for testing procedure as shown in Figure 3.

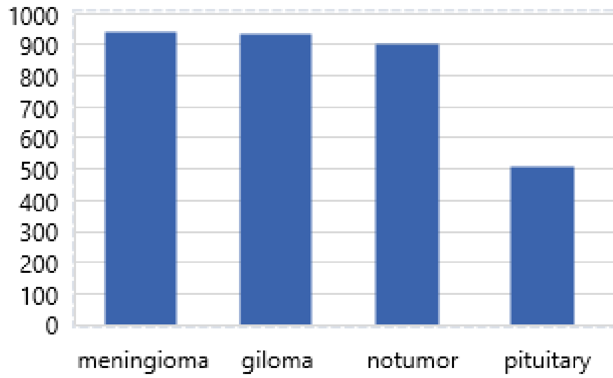
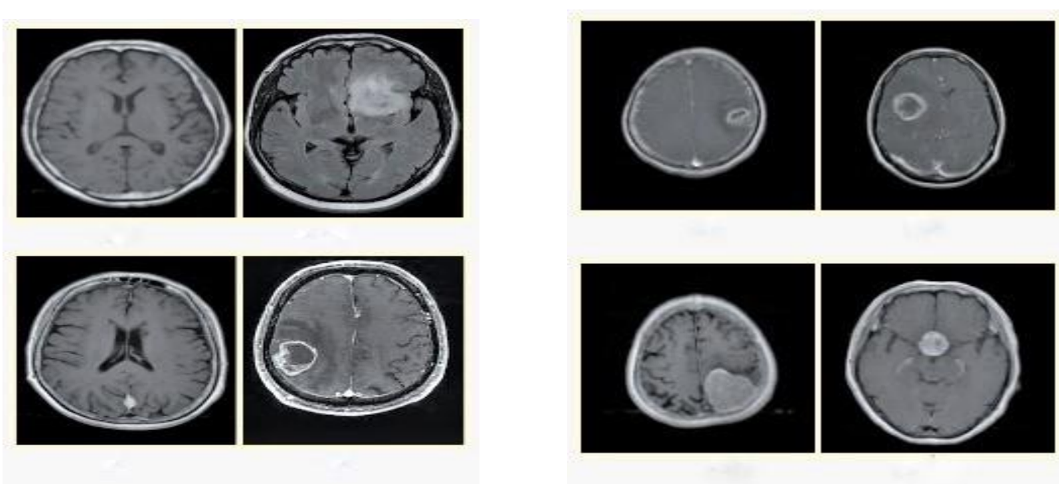


Figure 2: Dataset statistics (Class wise MRI image count).

3.3 Data Preparation

In our research project, data collecting is the most challenging duty. However, using algorithms after data gathering proved a significant challenge. Python code was utilized to do the given task. Unprocessed image data from the dataset makes it unsuitable for model training and prediction. To scale up every image in the dataset, the relevant data processing techniques are applied. Additionally, to ensure a quicker calculation Image figures is transformed into a NumPy array.



(a) (b)

Figure 3: Dataset images portion of training (a) and testing (b)

3.4 Research Subject and Instrumentation

More sophisticated and complex instruments are required as a result of the considerably increasing data sizes brought about by technological breakthroughs. There is a constant need for new approaches and instruments that can assist in turning huge data into useful information and knowledge, even while advances in Deep Learning technology have made large data collecting much more cautiously necessary. The idea and methods continue the tradition of giving users knowledge and practical experience in the theory and method of finding hidden patterns in huge datasets. In our research project "Brain Tumor Detection as well as Classification using Deep Learning from Magnetic Resonance Images" we have employing Deep Learning models such as EfficientNet, Xception, MobileNet, and ResNet-50 for finding the best results.

3.5 Used Deep Learning Model

The technique in use uses mri image data from epidermal cells to identify and categorize brain tumors. A number of pre-trained models, four individual Deep Learning Models these are EfficientNet, Xception, MobileNet, and ResNet-50, were used to classify brain tumors. In below discussed briefly those four models.

a) EfficientNet:

EfficientNet is a CNN design that employs complex parameters to scale equally across all directions. It makes connections between the various scaling components of the foundation network by using a grid search approach to get appropriate scaling values [28]. Modern convolutional neural network EfficientNet was made available as opensource through Google Brain. EfficientNet's greatest contribution has been to thoroughly test several scaling strategies for convolutional neural networks. For instance, one may increase the size of a ConvNet based on the breadth, depth, or resolution of the image input, or on a combining of all of those factors. One of most effective convolutional neural network for classification at the moment is EfficientNet. Furthermore, we select the input resolution before loading the model. Regarding GPU memory as well as to get feel for the categorization script, we start with 150 x150 here, but it might find it handy to scale this up for the assignment in future.

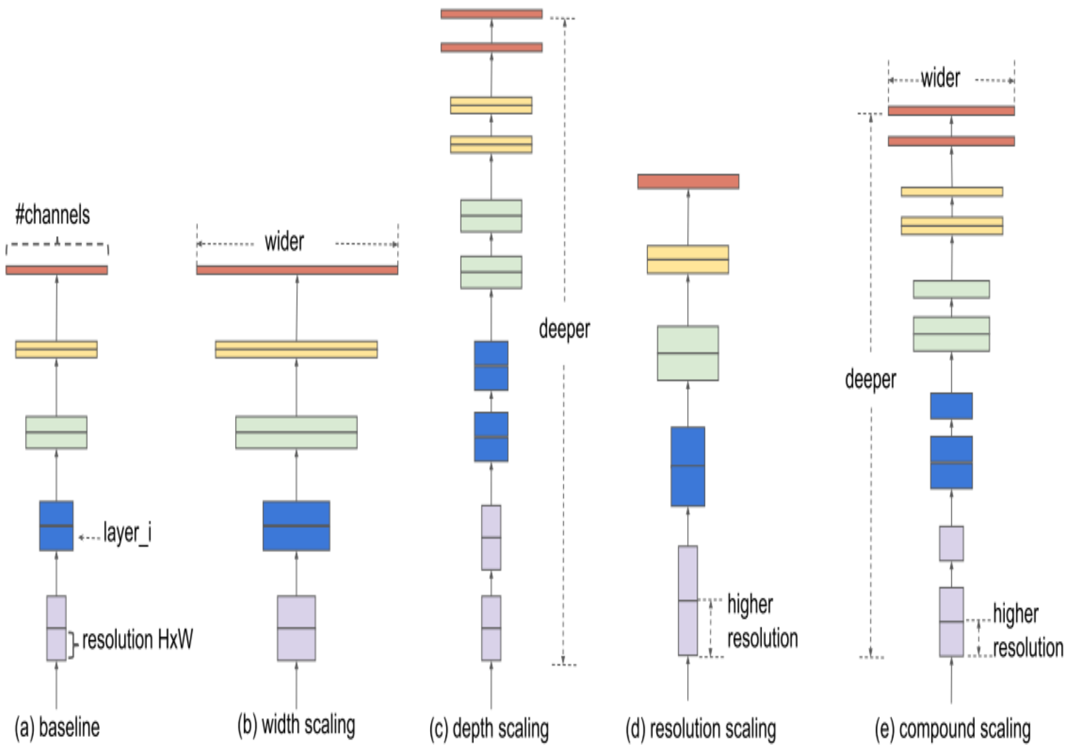


Figure 4: Architecture of EfficientNet Model.

We desire to research and reconsider how ConvNets are scaled up. We specifically look into the following fundamental query: Is there a logical approach to scaling up ConvNets that can produce higher accuracy and efficiency? Our empirical analysis demonstrates the importance of maintaining a balance across all network width, depth,and resolution parameters. Surprisingly, this balance may be attained by simply scaling each dimension with a fixed value [29]. We provide a straightforward yet efficient compound scaling approach in light of this observation. As disputed to conventional wisdom, which scales these factors arbitrarily, our approach scales network breadth, depth, and resolution evenly consuming a set of pre-defined mounting coefficients.

In the above figure usual scaling in (b) through (d) above simply increases one dimension of the network's width, depth, or resolution. The suggested complex scaling method (e) uses a set ratio to scale all three dimensions consistently. EfficientNets differed significantly from its predecessors thanks to the fundamental concept of compound scaling. Naturally, the idea of complex scaling also stands to reason since a high sample image with a better resolution will necessitate more channels and strands on the network in order to pick up the finer features of the bigger image.

b) MobileNet:

MobileNet is a CNN constructed pre-trained model. A model called MobileNets was developed mostly from depthwise separable convolutions, which were first introduced in and then employed in Inception models to lessen the amount of processing required in the top few layers [30]. The relationships between each of these terms are reported by MobileNet models. To start, it breaks the relationship between the size of the kernel and the amount of output channels using depthwise separable convolutions [31]. Regular convolution operations have the effect of integrating and filtering features created on the convolutional kernels to create a new portrayal. MobileNet is a model that filters pictures using convolution in a similar manner to that used by CNN in the past, but in a different method. This is divided into two layers by the depthwise separable convolution: a layer for merging and a layer for filtering. For this paper, Due to its ease of use and lower computational cost when compared to other optimizers, the Adam optimizer was utilized in the model during the training process.

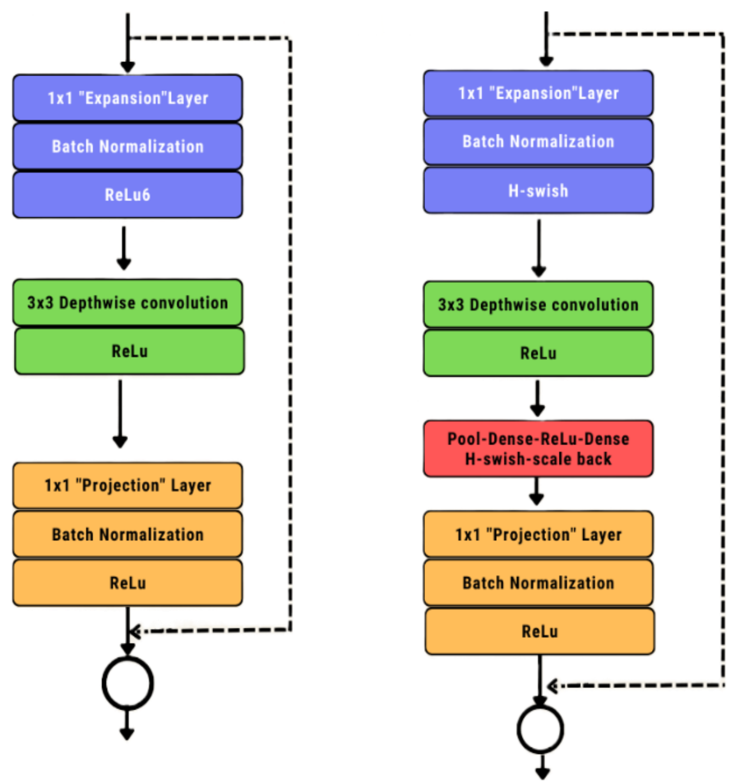


Figure 5: Architecture of MobileNet Model.

Following one or more fully linked layers, MobileNet is made up of a sequence of these depth-wise separable convolutions. Skip connections are also included in the model, which enhance its capacity to learn features at various sizes by enabling the result of one layer to ever be added straight to the output of another layer.

c) ResNet-50:

ResNet-50 was generated by Kaiming to enable deviations thinking skills, which is essentially the extraction of input characteristics from specific layers. Convolutional Neural Networks (CNN, or ConvNet), a kind of deep neural networks that is best frequently used to analyze visual vision, have a pre-trained deep learning approach known as ResNet-50 designed for classifying images [32]. ResNet-50, which has 50 layers, has been trained consuming a million photos from the ImageNet database in 1000 different kinds. The approach also boasts over 23 million learnable parameters, illustrating acomplex design thatenhances image recognition. The foundation of ResNets is to construct networks that are deeper than those of other simple networks while deciding on the ideal amount of layers to address the disappearance gradient issue.

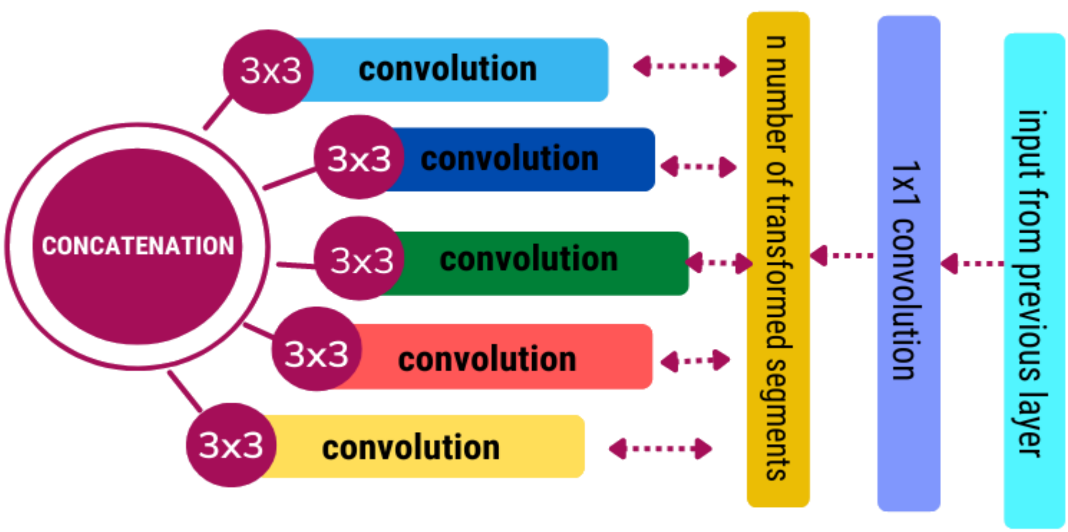


Figure 6: Architecture of ResNet50 Model.

d) Xception:

The deep convolutional neural network framework that makes up the pre-training model known as Xception. It was developed with Google's help, makes use of depth-wise distinct convolutions, and was made to explain CNN's Inception modules. A depthwise distinguishable convolution can be compared to an Inception module that has the most towers possible. With Inception modules replaced by depthwise separable convolutions, we suggest a revolutionary deep convolutional neural network design based on this finding [33]. There is yet another difference between Inception as well as Xception. Whether otherwise not there is a non-linearity following the original operation During Xception doesn't acquaint with any non-linearity, Inception model has a ReLU non-linearity that supports both procedures.

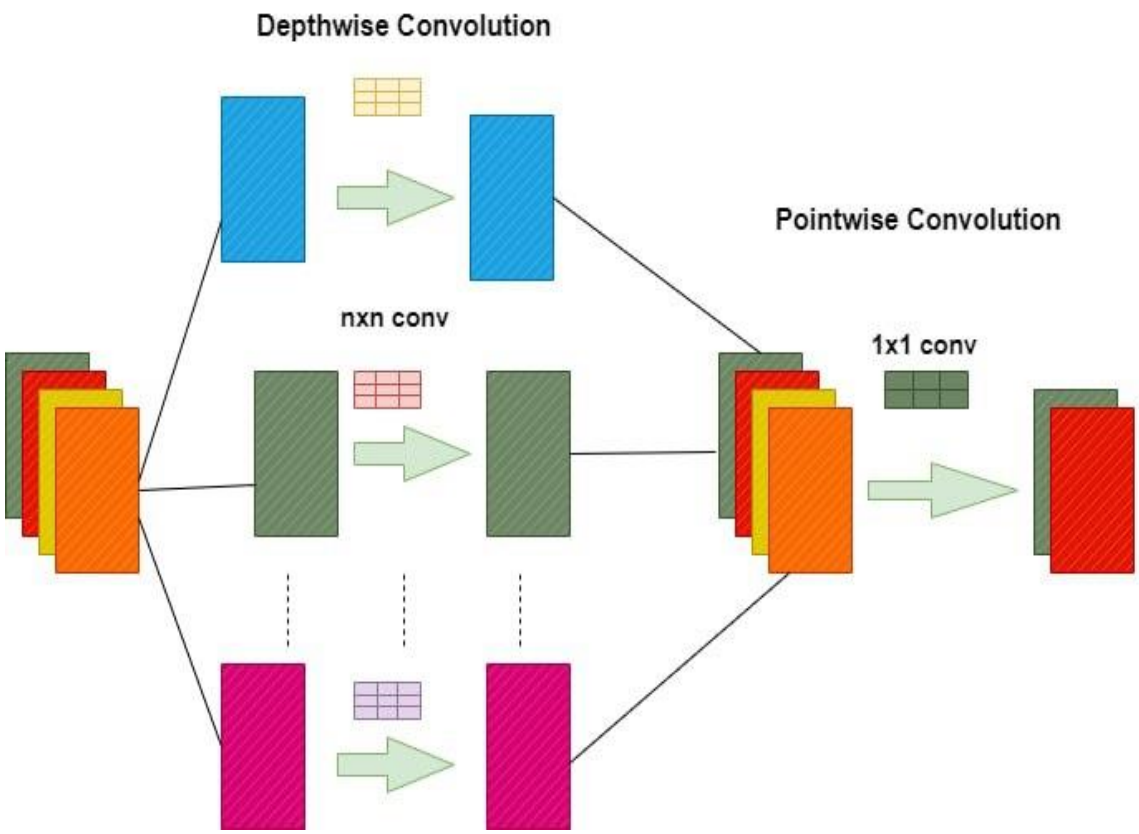


Figure 7: Architecture of Xception Model.

The depthwise convolution proceeded by the pointwise convolution is the unique depthwise independent convolution.

- The depth-wise computation is a channel-wise n-n spatially convolution. If the figure above had five channels, we would have five and a half n spatial convolutions.
- The 1×1 convolution used to modify the dimension is pointwise convolution.

We do not required to conduct convolution across all channels, as we would with conventional convolution. As a result, there are minimal relationships as well as the model is lighter.

3.6 Implementation Procedure:

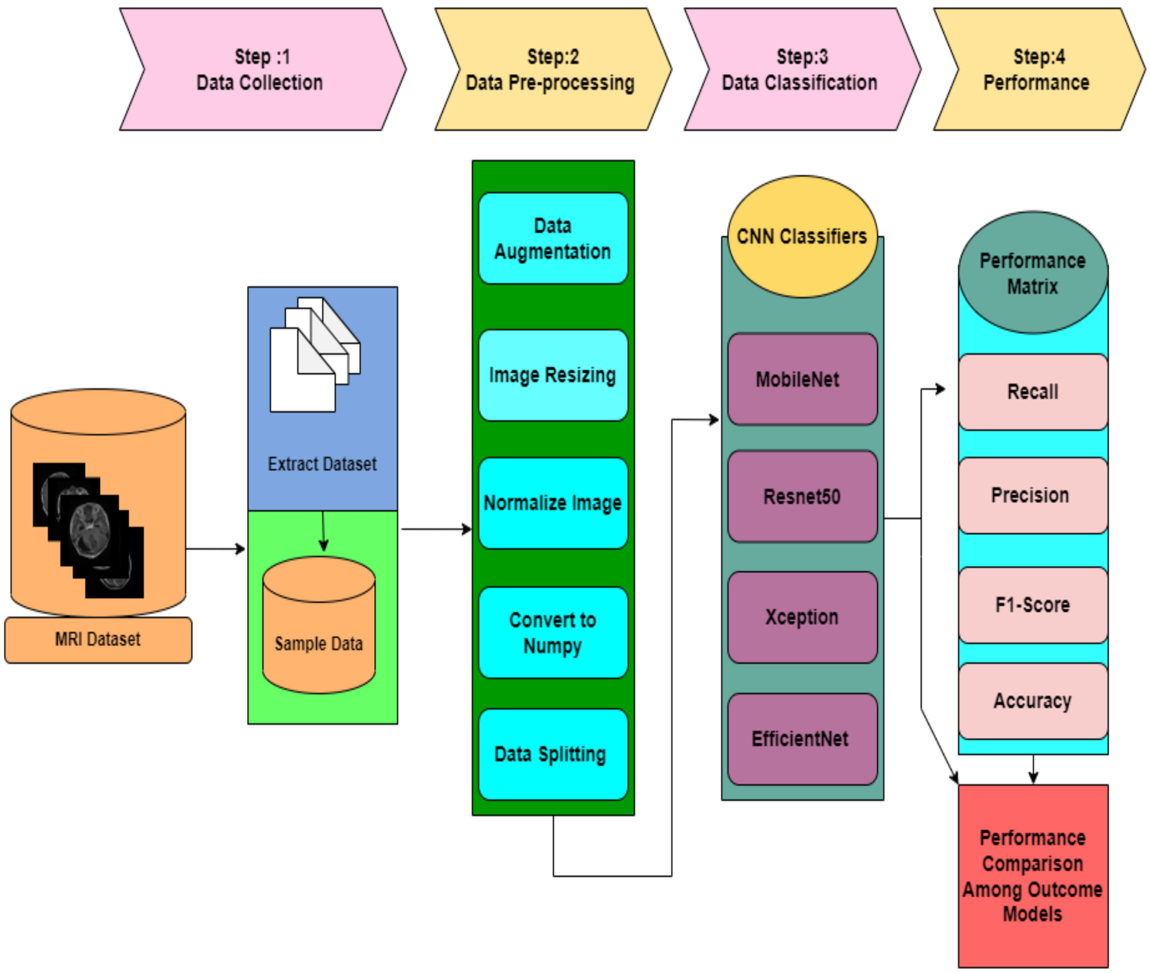


Figure 8: Working Process diagram of the proposed framework

In this procedure, we first create a clear diagram that lays out the steps for how we will complete our assignment. The diagram shows a clear path where we first begin the process and then get the Kaggle data set. We searched through various institutions in an effort to locate the real dataset, but were unsuccessful. As a result, we decided that if we could work with the demo data, we would gain experience working with the real dataset. For this reason, we continued to follow the flowchart diagram's instructions. We pre-process data by cleaning and filtering the datasets after they have been acquired because they are not yet ready to be used with algorithms. Next, we divided the datasets into two groups: training and testing, respectively. 20% of the data are used as testing datasets, while the remaining 80% are for training. Subsequently completing the procedure, we have applied four algorithms these are EfficientNet, Xception, MobileNet as well as ResNet-50. Among them, the higher accuracy found in EfficientNet approach.

CHAPTER 4
EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

Automating the identification of brain tumors has showed potential using deep learning, a sort of machine learning that includes training artificial neural networks on huge datasets. Deep learning techniques can learn to recognize patterns as well as traits typical of brain tumors by examining medical imaging data, such as that from magnetic resonance imaging (MRI).Pre-trained models such as EfficientNet, Xception, MobileNet and Resnet-50 can be executed to classify as well as predict all tumor cells Categories with efficiency. Not every model can produce precision at the same level. From each model, it differs. The proposed technique is contrasted with many other tactics that researchers have used on multiple datasets.

4.2 Experimental results & Analysis

After completing the training and testing procedures, the overall performance of the methodology is calculated based on accuracy, recall, precision, and F1-score.

4.2.1 Accuracy

Accuracy is a measure of the model's appearance throughout all classes. When every class is equally significant, it is advantageous. The overall number of forecasts divided by the amount of successful estimates yields this figure.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \quad (1)$$

As seen below, accuracy may also be evaluated in terms of positive as well as negative outcomes for binary classification.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

4.2.2 Precision

One measure of the model's performance is precision, or the class of a successful prediction performed by the model. When calculating precision, the fraction of true positives is distributed by the total quantity of positive predictions.

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

4.2.3 Recall

The recall is calculated as the percentage of Positive samples to each Positive instances that was accurately labelled as Positive. Recall evaluates the capacity of themodel to recognize positive samples. With more positive samples being discovered, the recall rises.

$$Recall = \frac{TP}{TP+FN} \tag{4}$$

4.2.4 F1-Score

The symmetrical mean of accuracy as well as recall is represented as the F1 score. Just a quick reminder that the symmetrical mean is a different measure from the more popular arithmetic mean. It is frequently helpful for calculating an average rate. In the F1 score, we evaluate the precision and recall standard deviation.

$$F1 = 2 * \frac{Precision*Recall}{Precision+Recall} \tag{5}$$

4.2.5 Confusion Matrix

A method for evaluating the effectiveness of a classification techniques is the confusion matrix. Classification accuracy alone may be deceptive if our dataset seems to have more than two classes or lower instances in certain categories than others. Our comprehension of the categorization models' accomplishments and shortcomings can be improved by developing a confusion matrix.

$$Confusion\ Matrix = \begin{bmatrix} TP & FP \\ FN & TN \end{bmatrix} \tag{6}$$

		Predicted	
		No Tumor	**Tumor**
Actual	**No Tumor**	True Negative (TN)	False Positive (FP)
	Tumor	False Negative (FN)	True Positive (TP)

Figure 9: Confusion matrix details.

$$where\ TP = True\ Positive, TN = True\ Negative, FP = False\ Positive, = False\ Negative$$

TABLE 2: OVERALL PERFORMANCE COMPARISON OF EACH MODELS.

Models	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1- Score (%)**
EfficientNet	98.18	98.18	98.25	98.20
Xception	97.23	98.24	97.05	97.12
MobileNet	96.96	97.89	97.89	97.90
ResNet50	95.66	97.60	97.60	97.65

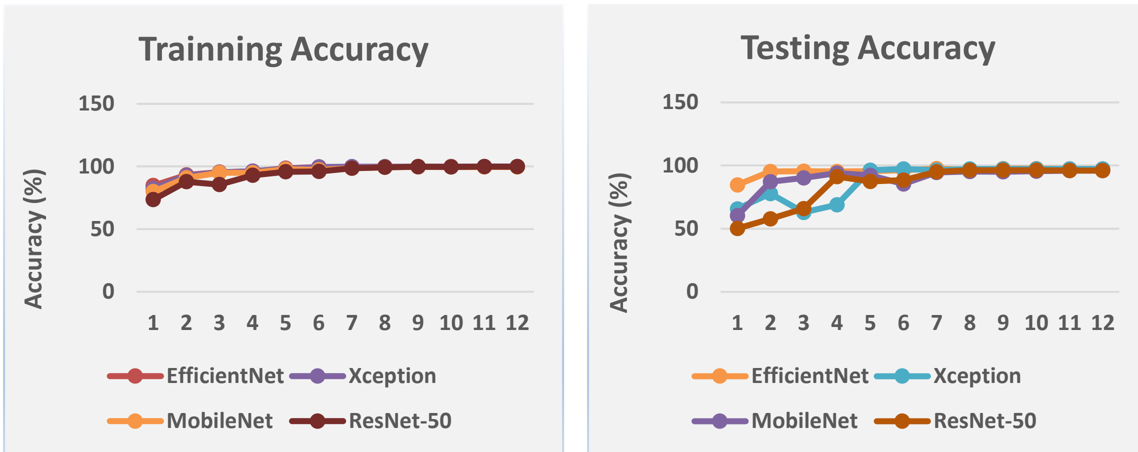
4.3 Descriptive Analysis

Pre-trained models such as EfficientNet, Xception, MobileNet and Resnet-50 can be executed to classify as well as predict all tumor cells Categories with efficiency. Not every model can produce precision at the same level. From each model, it differs. A total of 12 epochs were used to compute the result. The finding from the recording of each model reveals that, with the exception of the MobileNet framework, the top rating obtained for both training and testing data in every case was during the 12th epoch. The obtained results are shown in the table below for the methods EfficientNet, Xception, MobileNet, and Resnet-50, with EfficientNet recording the best accuracy of 97.64%. The 11th and 12th epoch calculations delivered the MobileNetV2 model's greatest accuracy of 95.96%. The accuracy rate of 97.31% obtained by Xception in the 6th, 8th, 9th, 10th, 11th, and 12th epochs is the greatest. ResNet-50 achieved its best accuracy, 96.30, in the 8th, 9th, and 10th epochs which is shown in table 3.

TABLE 3: TRAINNING-TESTING ACCURACY ANALYSIS FOR EACH EPOCH.

Epoch	EfficientNet		Xception		MobileNet		ResNet-50	
	Accuracy		Accuracy		Accuracy		Accuracy	
	Training (%)	Testing (%)	Training (%)	Testing (%)	Training (%)	Testing (%)	Training (%)	Testing (%)
1	84.68	84.71	82.21	65.66	79.88	60.27	73.46	50.17
2	93.09	95.28	92.68	77.78	91.03	87.21	87.80	57.91
3	95.53	95.60	95.31	62.96	94.97	90.24	85.62	65.99
4	95.91	95.28	96.25	69.02	95.01	93.94	92.91	91.25
5	98.65	95.62	97.94	96.30	97.75	92.26	95.65	87.54
6	99.47	96.30	99.66	97.31	97.41	85.52	95.91	88.55
7	99.70	97.63	99.74	96.30	98.50	94.61	98.65	94.95
8	99.55	96.63	99.81	97.31	99.29	95.29	99.44	96.30
9	99.59	97.64	99.81	97.31	99.74	94.95	99.74	96.30
10	99.74	97.64	99.81	97.31	99.70	95.62	99.59	96.30
11	99.81	97.31	99.77	97.31	99.47	95.96	99.89	95.96
12	99.81	97.31	99.92	97.31	99.47	95.96	99.85	95.96

We can see the pictorial view in the figure (a) and (b) of the training and testing accuracy that we acquire during run the model with value of epochs which is 12. Find that EfficientNet recording the best training accuracy of 99.81% and highest testing accuracy is 97.64% oberserved in EfficientNet and Xception.



(a) (b)

Figure 10: Training - Testing accuracy analysis graph for each epoch.

In compared to other models employed in this study, the statistic indicates that EfficientNet is the greatest model for predicting brain tumor and identifying tumor cells. For more understanding, the table below provides a general assessment of the pre-trained classifiers.

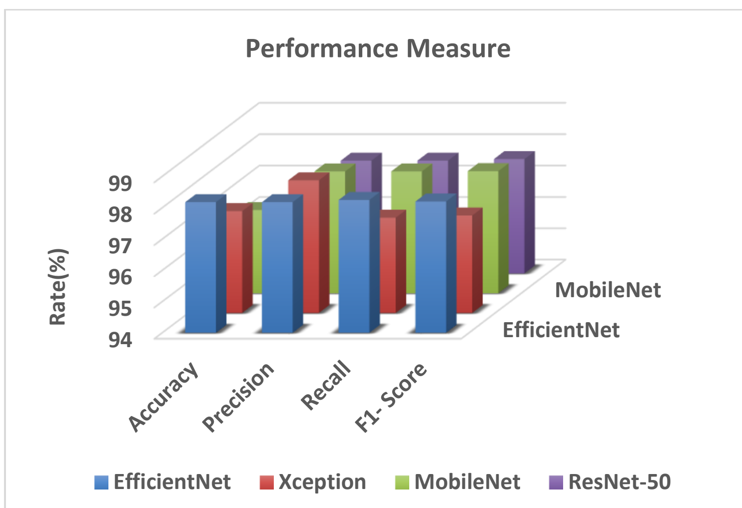


Figure 11: Perfomance measure graph for all models.

Throughout the entire application algorithm process, we have obtained our best outcome, which demonstrates the enormous sort of value that the F1 score, precision, sensitivity, and specificity have. EfficientNet achieved the best result, which is 98.18%, for the f1 score, which is composed of two fundamental features, precision and recall that are both calculated as percentages and merged as frequencies to assign a single number that is straightforward to understand and performs well in the accuracy matrix. This incredible precision will support in the early detection and characterization tumors.

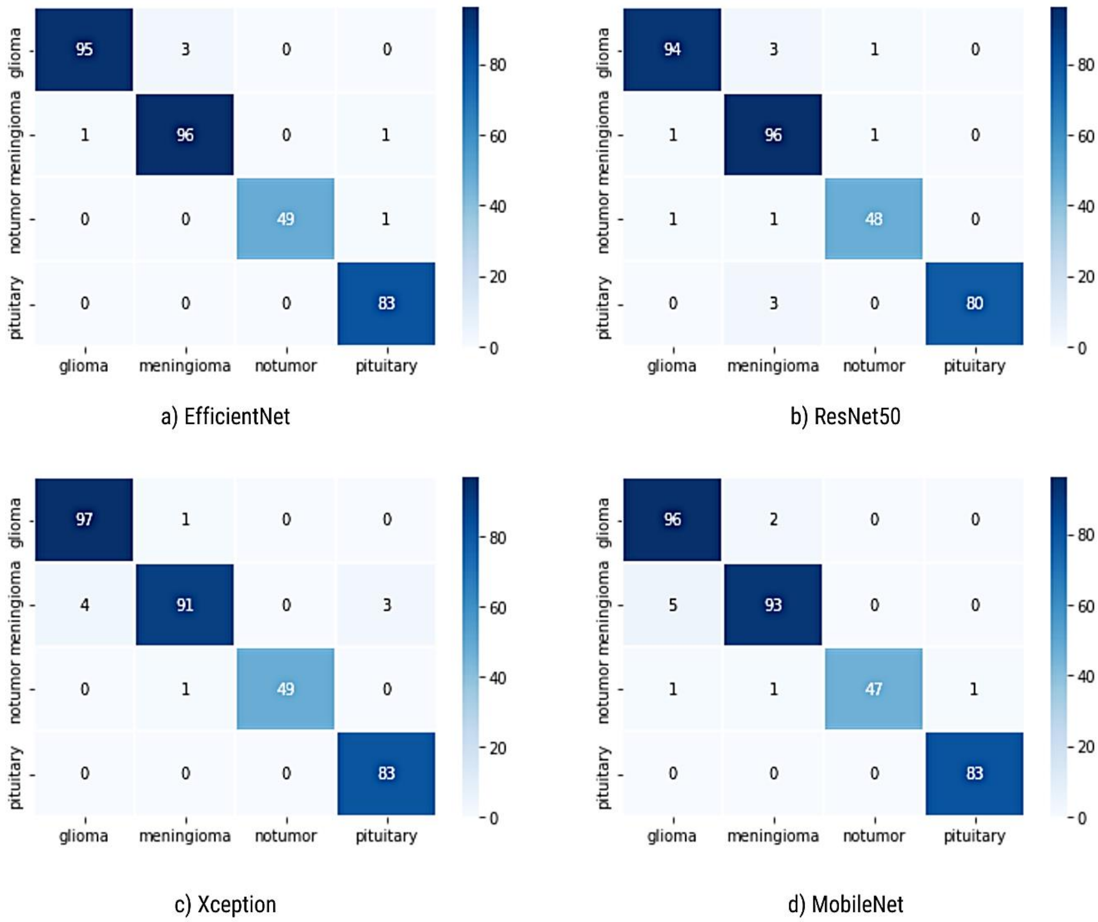


Figure 12: Confusion Matrix for each model.

CHAPTER 5
IMPACT ON SOCIETY ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

Deep learning has been applied to medical imaging to accurately categorize brain cancers. By increasing the speed and accuracy of diagnosis and providing patients with better treatment outcomes, this can have a tremendous impact on society. Using deep learning to classify brain tumors may have the potential to decrease the frequency of false negatives cases in which a tumor is not discovered. Early tumor detection and therapy may result from this, dramatically improving patient outcomes. Another advantage of deep learning is that it may be used to categorize tumors into several subtypes, which can help doctors decide on the best approach to treatment for a certain patient. For instance, some treatments may work better on some subtypes of gliomas than others. Deep learning can also help with the creation of tailored therapy by locating particular genetic or molecular markers linked to various tumor kinds. This may make it easier to customize treatments to meet the unique requirements of each patient, resulting in greater results and fewer adverse effects.It is important to keep in mind that deep learning is still a relatively new technology, and a number of obstacles must still be removed before it can be widely used in the medical industry. These obstacles include the requirement for vast quantities of high-quality data and the ethical issues raised by the application of AI in healthcare.

Overall, deep learning-based brain tumor classification has the capacity to have a substantial influence on society by improving patient outcomes and streamlining the diagnosis process.

5.2 Impact on Environment

Deep learning brain tumor categorization is unlikely to have an immediate effect on the environment. The energy needed to train as well as run these approaches is one significant environmental impact of using deep learning to classify brain tumors. Deep learning model training demands a sizable amount of processing power, which consumes energy. The handling of electronic waste could also be affected because deep learning gear is developing and updating so quickly. It is important to keep in mind, though, that the advantages of deep learning for classification of brain tumors such as better patient outcomes and shortened workload for medical staff, may also have a beneficial impact on the environment through lowering the demand for pointless medical procedures and the consumption of resources. Therefore, the environmental footprint of deep learning-based brain tumor categorization is insignificant and unrelated to the process itself, but it is still vital to take into account the larger environmental effects of deep learning and AI and adopt measures to minimize these influences as much as feasible.

5.3 Ethical Aspects

When utilizing deep learning to classify and diagnose brain tumors, there are a number of ethical issues to take into account. Massive amounts of medical imaging data, which contain sensitive personal data, must be accessed in order to employ deep convolutional neural network for brain tumor classification. To keep the confidence of patients as well as medical professionals, it is essential to ensure the security as well as confidentiality of this data. On the kaggle website, which was employed in this study, were the MRI imaging data. The quality of deep learning models depends on the data that are trained on. When AI is used in the medical field, there are concerns about who would bear accountability for any errors or incorrect diagnoses made by the AI system. For providing equal access to medical treatment, it is crucial to make sure that these technologies are available to all patients. Artificial intelligence in medical research presents ethical concerns about the use of human beings in research and the possibility of unexpected repercussions. One example is the utilization of deep learning with brain tumor categorization and recognition. Generally speaking, there are numerous and challenging ethical considerations when utilizing deep learning to classify brain tumors. It's crucial to thoroughly analyze these issues and take action to reduce any potential harmful effects.

5.4 Sustainability Plan

Take action to lessen the computation time of the deep learning approaches used to classify and identify brain tumors. Currently, there is no perfect solution to the issue of medical diagnosis, as well as diagnostic frameworks for brain tumors do not come without their flaws. Use strategies like fairness but also interpretability to make sure the models don't reinforce prejudices or discriminate against specific populations. Establish a comprehensive and traceable system, making sure that stakeholders are kept aware of the system's success and capturing all data and model variables so that you can track the choice the model made. In order to achieve the best performance as well as sustainability, it is important to continuously assess the deep learning models' productivity and viability and make the required adjustments. Work together to develop the field of deep learning-based brain tumor categorization and detection by exchanging information and resources with other researchers, medical practitioners, and industry experts.

CHAPTER 6
CONCLUSION AND FUTURE WORK

6.1 Conclusion

Brain tumor analysis and categorization is very critical in the field of medical science. In this regard, we introduce a methodology for detecting as well as classifying brain tumors that utilizes an ensemble of feature representation from deep convolutional neural networks (CNN). The presented methodology aims to get the maximum accuracy while maintaining the minimal computational complexity that might be a valuable strategy in further research and practical tumor diagnostic system. In order to help with the early identification and diagnosis of the problem, these automated system can evaluate the images as well as learn to recognize patterns and features characteristic of brain tumors. The classification results of the applied pre-trained models show that all of these methods are effective in identifying and forecasting image types in a unique way, but their respective scores differ. We used and evaluated the outcomes of various CNN classifiers, including EfficientNet, Xception, MobileNet, and ResNet-50 where EfficientNet has scored the maximum accuracy of 98.18%. This remarkable level of accuracy will help in the early identification of brain tumors depending on T1-weighted MR imaging scans. Meanwhile, this research can be further extended to determine the brain tumor types consuming MRI brain images using additional CNN models and the fine-tuning approach.

6.2 Future Work

The paper has been submitted to a journal a month ago. As we have more limitation for the work to clear the data set and further reply more algorithms but as we have not experienced it. So looking for further in the end that how can we applied more algorithm to get the best accuracy as well as doing hyperparameter tuning to get new model for detection brain tumor. This can help meet to solve this problem of Brain Tumor this disease all over the world not only this country.

References

[1] Siegel Rebecca, L., & Miller Kimberly, D. (2019). Jemal Ahmedin. Cancer statistics, 2019. CA: a cancer journal for clinicians, 69(1), 7-34.

[2] Díaz-Pernas, F. J., Martínez-Zarzuela, M., Antón-Rodríguez, M., & González-Ortega, D. (2021, February). A deep learning approach for brain tumor classification and segmentation using a multiscale convolutional neural network. In Healthcare (Vol. 9, No. 2, p. 153). MDPI.

[3] Raza, A., Ayub, H., Khan, J. A., Ahmad, I., S. Salama, A., Daradkeh, Y. I., ... & Hamam, H. (2022). A hybrid deep learning-based approach for brain tumor classification. Electronics, 11(7), 1146.

[4] Masood, M., Nazir, T., Nawaz, M., Mehmood, A., Rashid, J., Kwon, H. Y., & Hussain, A. (2021). A novel deep learning method for recognition and classification of brain tumors from MRI images. Diagnostics, 11(5), 744.

[5] Kumari, S., Karuppiah, M., Das, A. K., Li, X., Wu, F., & Gupta, V. (2018). Design of a secure anonymity-preserving authentication scheme for session initiation protocol using elliptic curve cryptography. Journal of Ambient Intelligence and Humanized Computing, 9(3), 643-653.

[6] Remy, L. (2018). Le parti ISLAM: filiations politiques, références et stratégies. Le parti Islam, 1-156.

[7] Van Eycke, Y. R., Balsat, C., Verset, L., Debeir, O., Salmon, I., & Decaestecker, C. (2018). Segmentation of glandular epithelium in colorectal tumours to automatically compartmentalise IHC biomarker quantification: A deep learning approach. Medical image analysis, 49, 35-45.

[8] Seetha, J., & Raja, S. S. (2018). Brain tumor classification using convolutional neural networks. Biomedical & Pharmacology Journal, 11(3), 1457.

[9] Mzoughi, H., Njeh, I., Wali, A., Slima, M. B., BenHamida, A., Mhiri, C., & Mahfoudhe, K. B. (2020). Deep multi-scale 3D convolutional neural network (CNN) for MRI gliomas brain tumor classification. Journal of Digital Imaging, 33(4), 903-915.

[10] Sharif, M. I., Li, J. P., Khan, M. A., & Saleem, M. A. (2020). Active deep neural network features selection for segmentation and recognition of brain tumors using MRI images. Pattern Recognition Letters, 129, 181-189.

[11] Narmatha, C., Eljack, S. M., Tuka, A. A. R. M., Manimurugan, S., & Mustafa, M. (2020). A hybrid fuzzy brain-storm optimization algorithm for the classification of brain tumor MRI images. Journal of ambient intelligence and humanized computing, 1-9.

[12] Pandey, S. (2021). Brain tumor detection using CNN. Turkish Journal of Computer and Mathematics Education (TURCOMAT), 12(11), 4597-4603.

[13] Banerjee, S., Mitra, S., Masulli, F., & Rovetta, S. (2019). Deep radiomics for brain tumor detection and classification from multi-sequence MRI. arXiv preprint arXiv:1903.09240.

[14] Sajjad, M., Khan, S., Muhammad, K., Wu, W., Ullah, A., & Baik, S. W. (2019). Multi-grade brain tumor classification using deep CNN with extensive data augmentation. Journal of computational science, 30, 174-182.

[15] Sultan, S., Taimuri, U., Basnan, S. A., Ai-Orabi, W. K., Awadallah, A., Almowald, F., & Hazazi, A. (2020). Low vitamin D and its association with cognitive impairment and dementia. Journal of aging research, 2020.

[16] Bernal, J., Kushibar, K., Asfaw, D. S., Valverde, S., Oliver, A., Martí, R., & Lladó, X. (2019). Deep convolutional neural networks for brain image analysis on magnetic resonance imaging: a review. Artificial intelligence in medicine, 95, 64-81.

[17] Kshirsagar, P. R., Rakhonde, A. N., & Chippalkatti, P. (2020). MRI image based brain tumor detection using machine learning. Test Engineering and Management, 81, 3672-3680.

[18] Ma, C., Luo, G., & Wang, K. (2018). Concatenated and connected random forests with multiscale patch driven active contour model for automated brain tumor segmentation of MR images. IEEE transactions on medical imaging, 37(8), 1943-1954.

[19] Afshar, P., Plataniotis, K. N., & Mohammadi, A. (2019, May). Capsule networks for brain tumor classification based on MRI images and coarse tumor boundaries. In ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (pp. 1368-1372). IEEE.

[20] Zhang, D., Huang, G., Zhang, Q., Han, J., Han, J., & Yu, Y. (2021). Cross-modality deep feature learning for brain tumor segmentation. Pattern Recognition, 110, 107562.

[21] Thayumanavan, M., & Ramasamy, A. (2021). An efficient approach for brain tumor detection and segmentation in MR brain images using random forest classifier. Concurrent Engineering, 29(3), 266-274.

[22] Nayak, D. R., Padhy, N., Mallick, P. K., Zymbler, M., & Kumar, S. (2022). Brain Tumor Classification Using Dense Efficient-Net. Axioms, 11(1), 34.

[23] Gaur, L., Bhandari, M., Razdan, T., Mallik, S., & Zhao, Z. (2022). Explanation-Driven Deep Learning Model for Prediction of Brain Tumour Status Using MRI Image Data. Frontiers in Genetics, 448.

[24] Baur, C., Graf, R., Wiestler, B., Albarqouni, S., & Navab, N. (2020, October). Steganomaly: Inhibiting cyclegan steganography for unsupervised anomaly detection in brain mri. In International conference on medical image computing and computer-assisted intervention (pp. 718-727). Springer, Cham.

[25] Ranjbarzadeh, R., Bagherian Kasgari, A., Jafarzadeh Ghoushchi, S., Anari, S., Naseri, M., & Bendechache, M. (2021). Brain tumor segmentation based on deep learning and an attention mechanism using MRI multi-modalities brain images. Scientific Reports, 11(1), 1-17.

[26] Pandey, Saumya. "Brain tumor detection using CNN." Turkish Journal of Computer and Mathematics Education (TURCOMAT) 12, no. 11 (2021): 4597-4603.

[27] https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset

[28] Analytics IndiaMag, Implementing EfficientNet: A Powerful Convolutional Neural Network, Accessed: March 12, 2022, Available: https://analyticsindiamag.com/implementing-efficientnet-a-powerful-convolutional-neural-network/

[29] Francois Chollet ."Xception: Deep Learning with Depthwise Separable Convolutions" - 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) – 2017.

[30] Wei Wang, Yutao Li, Ting Zou, Xin Wang, Jieyu You, Yanhong Luo, "A Novel Image Classification Approach via Dense-MobileNet Models", Mobile Information Systems, vol. 2020, Article ID 7602384, 8 pages, 2020. https://doi.org/10.1155/2020/7602384

[31] Anaraki, Amin Kabir, Moosa Ayati, and Foad Kazemi. "Magnetic resonance imaging-based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms." biocybernetics and biomedical engineering 39.1 (2019): 63-74.

[32] Dheir, I. M., et al. (2020). "Classifying Nuts Types Using Convolutional Neural Network." International Journal of Academic Information Systems Research (IJAISR) 3(12): 12-18.

[33] Francois Chollet ."Xception: Deep Learning with Depthwise Separable Convolutions" - 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) – 2017.

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