COMPARATIVE ANALYSIS OF MULTIPLE PRETRAINED CNN MODELS TO IDENTIFY HUMAN BRAIN TUMOR THROUGH DEEP LEARNING.

BY

YEASIN BHUIYAN

ID: 191-15-12297

MD ABDULLAH AL NOMAN

ID: 191-15-12758

AND

SADIA AFROSE

ID: 191-15-12680

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

Supervised By

MAYEN UDDIN MOJUMDAR
Lecturer
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

JANUARY 2023

APPROVAL

This thesis titled **"Comparative Analysis Of Multiple Pretrained CNN Models To Identify Human Brain Tumor Through Deep Learning"**, submitted by Yeasin Bhuiyan, ID: 191-15-12297, Md Abdullah Al Noman, ID: 191-15-12758 and Sadia Afrose, ID: 191-15-12680 to 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 *28th January, 2023.*

BOARD OF EXAMINERS

4/2/23

Dr. Touhid Bhuiyan — **Chairman**
Professor and Head
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Nazmun Nessa Moon — **Internal Examiner**
Associate Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Zakia Sultana — **Internal Examiner**
Senior Lecturer
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Dr. Shamim H Ripon — **External Examiner**
Professor
Department of Computer Science and Engineering
East West University

DECLARATION

We hereby declare that, this thesis has been done by us under the supervision of **Mayen Uddin Mojumdar, Lecturer, Department of CSE** Daffodil International University. We also declare that neither this thesis nor any part of this thesis has been submitted elsewhere for award of any degree or diploma.

Supervised By:

Mayen Uddin Mojumdar
Lecturer
Department of CSE
Daffodil International University

Submitted By:

Yeasin

Yeasin Bhuiyan
ID: 191-15-12297
Department of CSE
Daffodil International University

Noman.

Md Abdullah Al Noman
ID: 191-15-12758
Department of CSE
Daffodil International University

Sadia Afrose

Sadia Afrose
ID: 191-15-12680
Department of CSE
Daffodil International University

ACKNOWLEDGEMENT

First, we express our heartiest thanks and gratefulness to Almighty God for His divine blessing that makes us possible to complete the final year project/internship successfully.

We really grateful and wish our profound indebtedness to **Mayen Uddin Mojumdar, Lecturer**, Department of CSE**,** Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of "Deep Learning" to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stages have made it possible to complete this project.

We would like to express our heartiest gratitude to **Mayen Uddin Mojumdar, Lecturer**, Department of CSE and **Professor Dr. Touhid Bhuiyan**, Head, Department of CSE, for his kind help to finish our project and also to other faculty members and the staff of the CSE department of Daffodil International University.

We would like to thank our entire course mate in Daffodil International University, who took part in this discussion while completing the course work.

Finally, we must acknowledge with due respect the constant support and patients of our parents.

ABSTRACT

The tumor of brain is a severe disease condition caused by uncontrolled and improper cell division. One of the most deadly and severe cancers that can affect both adults and children is the brain tumor. Timely and precise diagnosis of the tumors presence in brain can help in treatment process. Identifying the brain tumors is among the major essential and tough responsibilities in the field of handling medical image because physical identification with human assistance may result in incorrect prognosis and diagnosis. The use of Computer Aided Diagnosis with the aim to detect tumors of brain has gained attention due to recent advancements in the technology. The health sector has benefited from deep learning application for the diagnosis of numerous disorders regarding medical images. Our research study's goal is to use MRI scans to identify tumors of brain using a deep neural network approach. Convolutional Neural Networks (CNN), a type of deep learning network model, are used in the diagnosis process. We will use a variety of CNN model designs in this research, including ordinary CNN, InceptionV3, MobileNetV2, DenseNet201, ResNet50, ResNet101, VGG19. Scarcity of data is a fact, so we collected brain tumor MRI image data from Kaggle and merged different image files. We applied data augmentation to enhance the amount of MRI data since deep learning networks perform better when they are trained on a big amount of data. A comparative analysis of the accuracy of different models were done to come in a conclusion about which model provides the greatest accuracy in detecting brain tumors from MRI images. DenseNet201 with 99% accuracy has outperformed the accuracy among the evaluated pretrained methods. It will help the physicians to early detect Brain Tumor more precisely using DenseNet201 architecture.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

Introduction

1.1 Introduction

Human brain, the most important organ of our body which is comprised of billions of nerve cells. The brain serves as a command center and is a vital part of the neurological system that carries out daily tasks. The brain gathers impulses or signals from the sensory part of human body and processes the signals to give a decision [1]. The cerebellum, brainstem, and cerebellum are the three sections of the brain. Gray matter, white matter, and cerebrospinal fluid are the three types of tissues that make up the human brain [2]. Any defects or disease that affects the brain could have adverse effects. Different factors, such as congenital abnormalities, a concussion experienced in an injury, or UCG (Uncontrolled Cell Growth) in a central brain area, might cause the brain's normal condition to be hampered.

The physiological system may experience a variety of issues due to an irregularity, and an untreated brain anomaly. UCG-induced brain abnormalities pose a serious risk, and unchecked growth will result in brain cancer, one of the cancer burdens that are quickly rising internationally [3].

Abnormal expansion of mass which forms within the brain and is specifically impacted by the tissues in the skull or brain's subarachnoid space is called a brain tumor. Brain tumor is one of the most lethal disorders, because it has a lesser chance of survival and is more violent than other forms of tumors. Brain tumors are classified into two types: one is benign which is non-cancerous and the another one is malignant which is cancerous. Loss of memory, persistent headaches, inability to concentrate and coordination issues are some of the common manifestations and signs of brain tumors. Compared to other cancers like breast and lung cancer, brain tumors are less common [4].

According to [5], It is estimated that 308,102 people worldwide were diagnosed with a primary brain or spinal cord tumor by 2020. The 10th biggest cause of death for both sexes is cancer of the neurological system, including the brain. Primary malignant brain and CNS tumors are predicted to kill 18,280 people in the United States this year (10,710 males and 7,570 women). Malignant brain and other CNS tumors were responsible for 83,029 deaths in the US between 2014 and 2018 [6].

So, brain tumor is a disease that is becoming more and more lethal, thus early detection is essential for a successful treatment strategy. Early detection of a brain tumor, doctors may be able to treat the patient and help them survive or beat it. However, due to their small size, brain tumors are difficult for humans to detect in the early stages. Yet, human evaluation is not always precise, and it takes a lot of time. Moreover, manual diagnosis of brain tumor is a quite challenging task. Advancement of CAD (Computer Aided Diagnostic) tools in diagnosing diseases have attracted the researchers to focus on brain tumor detection using CAD.

Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography (PET), Electroencephalogram (EEG), and other tests are used to diagnose brain tumors at the clinical level. The most popular and efficient technique is magnetic resource imaging (MRI). MRI creates interior images of the body's organs by using powerful magnetic fields and radio waves. Due to many different modalities and the fact that the brain tumor is clearly visible in a brain MRI compared to other procedures, MRI is by far the most popular method. In order to assess the numerous brain abnormalities, including the brain tumor, MRIs are often preferred [7].

Identification of brain tumor from MRI scans is a laborious and time-consuming task, when human or manual approach is followed. In addition, inaccurate identification will lead to vital consequences as there remains a greater chance of being misidentification when manual identification is done. Researchers are now concerned about the introduction of CAD techniques in brain tumor diagnosis from MRI scans. Because of advances in artificial intelligence and deep learning, the field of medical has advanced significantly within the recent years. One instance is the processing of medical images approach, that makes disease diagnosis easier and faster than in the old days. Computer-aided technology is therefore essential to overcome the challenges because the medical sector need well planned and trustworthy methods for the diagnosis of cancer-like fatal disease. Use of CAD tools have aided much to remove the traditional mistakes that are done by human assessment [7,8].

The two primary methods used for brain tumor detection are Machine Learning (ML) and Deep Learning (DL) [1]. When working with enormous datasets, machine learning classifiers need a lot of time and memory. Conventional machine learning (ML) methods dependent on features that have been hand-crafted, which is reducing the solution’s stability [9]. Performance of the deep learning-based algorithms, however, is considerably superior because they automatically extract meaningful features. Deep learning can classify histopathology images as a (deep) feature extractor leading to a diagnosis [10]. In the field of bioinformatics, deep learning algorithms, in particular CNN, have demonstrated amazing performance. Among the most popular deep learning (DL) models, Convolutional neural networks (CNNs) and its derivatives have been used to evaluate various medical images. Three basic layers make up the CNN: a pooling layer reduces the map of feature dimensions, classification is performed via a fully connected (FC) layer, and each convolution layer extracts features [4].

Applying DL to medical issues can be difficult due to a scarcity of training data. Data augmentation is a popular method for solving this issue. It functions by using a variety of approaches to generate new training data from the current data [11]. The technique can be carried out in a variety of ways, including by rotating, flipping, shearing, and introducing random noise, among others [2]. The new photos in the dataset will assist in training the network and improve the accuracy of categorizing test data. This study uses data augmentation because there is not sufficient amount of MRI scans of brain tumors. The growth of tumor at primary stage can be very tiny in size, so a complex problem may arise regarding the identification of tumor. Our research work has solved the problem as the models are trained with a large number of datasets.

By utilizing pretrained CNN models, this paper contributes to the field of brain tumor identification via deep learning. The research work is summarized here as follows:

- The Kaggle repository website is used to collect different MRI data related to brain tumors. The number of cases was increased using a data augmentation strategy, which will aid in more effective model training.
- On the basis of the brain tumor MRI data, seven different pretrained CNN models (ordinary CNN, InceptionV3, MobileNetV2, DenseNet201, ResNet50, ResNet101, VGG19) were implemented to identify brain tumors.
- To determine which model performs better in brain tumor identification, the seven algorithms' percentages of accuracy have compared.
- Suggested the top accuracy model for identify brain tumors, to supporting medical industry in selecting among the numerous algorithms.

1.2 Motivation

We were looking for domains to use as research topics as part of our research study. We had ideas about how we could help people through our research. Then we discovered that the integration of technology with medical image recognition is a hot topic. As a result, we chose to work with brain tumors. Main goal of this study is, to support the medical industry by finding a high-performing algorithm for detecting brain tumors. We considered using deep learning techniques to detect brain tumors, which would benefit people in the medical field. Brain is the most vital and important organ in the human body. The brain is the primary control center for all sensory nerves and serves as a processing unit in the human body. All activities and functions, whether internal or external, are controlled by the brain. Any illness affecting the brain is cause for concern. Brain tumor is an abnormal mass or tissue expansion within the cerebral hemisphere. This tumor may be benign or malignant which represent respectively non-cancerous or cancerous. The implications of a brain tumor in the human body might be dangerous if not treated early. Because of this, early detection of a brain tumor is essential in order to treat the patient and save his or her life. Since manual identification of brain tumors takes time and effort, we attempted to use deep learning techniques to identify brain tumors.

1.3 Objective of Research

a) To identify brain tumors from MRI images using deep learning and convolutional neural network methods.
b) A comparison examination of the results of the used pre-trained CNN models for the same dataset will aid in determining the best performing model to identify brain tumors.

1.4 Research Question

a) What will happen if a brain tumor grows irregularly?
b) How is brain cancer attacking the patient as a result of the tumor?
c) How many people have died globally as a result of a brain tumor?
d) How can computer-aided tools be used to precisely identify brain tumors?
e) What will be our data source for gathering information about brain tumors?
f) What strategies can be followed to mitigate the scarcity of image data available for brain tumor?
g) Which field, machine learning or deep learning, should be used to identify brain tumors using CAD?
h) Which deep learning algorithms or models should be used to produce better results?

i) What amount of data should be organized under training testing and validation?
j) Which model is the most accurate for identify brain-tumors from MRI images of the brain?
k) How can we increase the detection accuracy of pre-trained deep learning models in the instance of brain tumor identification?

1.5 Expected Output

a) Capable of recommending the highest performing algorithm for brain tumor detection, which will aid physicians in making a knowledgeable choice among the available classifiers.
b) By overcoming the issue of a shortage of data for brain tumors, deep learning models are trained effectively.

1.6 Report Layout

Brief description of the chapters of this report is given in this section.

Chapter 1: Introduction

This chapter describes about the introduction of brain tumor, motivation behind our work, research question, objectives and expected outcomes from the study.

Chapter 2: Background Study

This chapter describes about the preliminary idea, literature review of previous works, summary, scope of problem and challenges faced during the research study.

Chapter 3: Research Methodology

This chapter describes about instrument and subject related to research, Dataset, applied methodology, requirement to implement the research.

Chapter 4: Experimental Result and Discussion

This chapter describes about the experimental setup, result analysis and discussion about the results.

Chapter 5: Impact on Society, Environment and Sustainability

This chapter describes about the impact of this research on society and environment, ethical aspect regarding the study and plan to sustain the study.

Chapter 6: Summary, Conclusion, Recommendation and Implication for Future Research

This chapter describes about the whole summary of our study, conclusion and scope for future research.

CHAPTER 2

Background

2.1 Preliminaries

Brain is the most important organ of our body. It serves as the primary control and command center for the entire nervous system. Illness caused by brain tumors has increased at frightening rate in recent years. Brain tumors claim the lives of people all over the world. Brain tumor not only affects the patient's body, but the patient's family must also struggle with financial solvency in order to treat brain tumor. The magnetic resonance image of the brain is usually used to detect brain tumors. Doctors or physicians detect brain tumors using a time-consuming and laborious traditional approach. Human intervention to detect brain tumors is also a risky endeavor. As a result, researchers are constantly working to integrate brain tumor detection with automated detection systems through the computer aided diagnosis process. We investigated research papers 40 recent on brain tumor detection using CAD. Many algorithms have been introduced in papers, but the workings still have some limitations. We are working to tackle the issue of limits by introducing several techniques. In the literature review section, we analyzed the work of 20 research papers.

2.2 Literature Review

Medical image analysis has greatly benefited from the evolution of new deep learning-based technologies, particularly in the area of disease diagnosis. Deep learning is commonly utilized in image processing techniques to segment, identify, and categorize MRI images, as well as to identify and detect brain tumors. CNN has been utilized extensively to handle a variety of issues, but its performance for image processing in health applications is excellent.

Some of the recent approaches that followed DL-CNN are:

Raza et al. [1] DeepTumorNet is a hybrid deep learning network proposed for the classification of three types of brain tumors (BTs): glioma, meningioma, and pituitary tumors. In this study authors have used GoogleNet architecture of the CNN as a base to develop their model where the modification they have removed the remaining five layers of GoogleNet and adding new fifteen layers as an alternative. The suggested model was implemented on freely accessible CE-MRI dataset and obtained accuracy of 99.67% which outperformed the other new techniques for brain tumor identification.

Sahu et al. [2] enhanced the size of brain image dataset (255 brain scans, 155 of which show a brain tumor, the remaining images being tumor-free.) by performing data augmentation. A CNN model was implemented on the augmented dataset. The authors have tested the model by integrating 12 various combinations of optimizers, activation functions, and loss function. The authors got to the conclusion that binary cross entropy is the btter performer as the loss function and exhibits the maximum accuracy when Relu and Sigmoid and loss functions are combined where time was the considerable factor. Conversely, Hinge loss as the loss function consistently produced the lowest results. The optimizers for Adam and Nadam both performed similarly, however Adamax had very poor results.

Rajinikanth et al. [3] introduced a novel VGG19 network with handcrafted features and serially-fused deep features. When compared to other Deep learning architectures, VGG19 had better results. VGG19 accuracy were improved by substituting the classifier of Softmax by decision tree, k-nearest Neighbor, SVM-linear and SVM-RBF followed by implementation of future fusion technique to improve detection accuracy.

Asif et al. [4] proposed an effective deep learning-based framework to classify brain tumor by following transfer learning approach to avoid training model from scratch. Features were extracted using pretrained models like Xception, NasNet Large, DenseNet121, and InceptionResNetV2. The authors transferred the extracted features to their own customized model to detect brain tumor with better accuracy.

Khan et al. [7] developed a basic CNN model of 8 convolutional layer. The proposed model was trained on a dataset which contains 253 brain MRI images after performing data augmentation and image processing. Comparing the result of proposed model with pre-trained VGG-16, ResNet-50, and Inception-v3 models it was concluded that the proposed strategy has outperformed all the others pretrained model by achieving accuracy of 100%. The training time per epoch was lowered by the authors to 205 seconds, which is a significant reduction over the widely used CNN models.

Hossain et al. [8] introduced two models. The first model utilized machine learning to identify and segmental brain tumor. The Fuzzy C Means method was used to segment the brain tumor, along with skull stripping, filtering and enhancement, morphological procedures, tumor contouring, feature extraction, and classification using conventional classifiers. The second model proposed by the authors is a five layers CNN model to detect Brain tumor. The models were evaluated on BRATS dataset containing 187

2DMRI image with tumor and 30 images with no tumor. The authors have obtained accuracy of 92.42% with Support Vector Machine (SVM) and accuracy of 97.87% with Convolutional Neural Network (CNN).

Sharma et al. [10] developed a unique approach for deep feature extraction and classification of brain tumors utilizing the customized ResNet50 algorithm in conjunction with the Enhanced Watershed Segmentation (EWS) algorithm. ResNet50 was utilized as the base model, and it was improved by adding three fully connected layers and five convolutional layers. EWS-based customized ResNet50 algorithm and hybrid deep feature-based ResNet50 algorithm obtained accuracy of 90% and 92% individually.

Lu et al. [11] developed a unique strategy for removing the absence of training data in Magnetic Resonance Spectroscopy of brain tumors through data distillation and augmentation. Data augmentation enhanced the quantity of data and a data distillation method filtered out noisy labeled data. By employing deep neural networks, the suggested technique has achieved accuracy comparable to that of human experts.

Noreen et al. [12] suggested a model to classify brain tumors by eliminating the inception module from InceptionV3's lowest layers and concatenating features there. The lower and upper dense blocks of the brain tumor dataset were utilized to extract features using DenseNet201. Following feature extraction, these characteristics were concatenated and put into the softmax classifier for brain tumor identification and assessment. The suggested approach yielded the best results in brain tumor identification, with a testing accuracy of 99.51% on test samples.

Hu et al. [13] developed a design of an optimized classifier on the basis of deep belief network using an updated Seagull optimization approach to detect brain tumor. The dataset in the research article was preprocessed by the authors to minimize noise and provide better image quality, followed by utilizing the Kapur thresholding method for the brain tumor segmentation. Features were retrieved from the image, and the author used the improved version of Seagull Optimization Algorithm to get the best feature selection. In the meantime, an improved deep belief network was used to categorize the MR brain tumor picture dataset into brain tumor and normal brain. The suggested technique outperformed the other examined methods, with a correct detection rate of 88%.

Choudhury et al. [14] has been presented a three-layered CNN model architecture that will ultimately be coupled to fully connected neural networks. The proposed method's main objective was to distinguish between different Brain MRI pictures to ascertain whether or not they were tumorous. The proposed model is based on Keras, with Tensor Flow serving as its backend. The 35 epochs of the three-layered model produced the results with relatively little pre-processing. The model's accuracy was 96.08%, and its f-score was 97.3.

Woźniak et al. [15] introduced a novel correlation learning mechanism (CLM) for deep neural network designs that combines convolutional neural network (CNN) with traditional architecture, allowing the principal neural classifier to learn faster and operate more effectively. For their investigation, the scientists used two datasets: 3064 pictures of brain tumors reflecting three distinct classes of brain cancers and the Brain MRI dataset from Kaggle. The model concept based on a correlation learning mechanism outperformed with an accuracy of 97.5%.

Çinar et al. [16] to build a hybrid model, CNN's ResNet50 architecture was changed. The Resnet50 model's last five layers have been removed, and 10 additional levels have been included. To assess the accuracy of their proposed model, the authors additionally employed CNN models, Alexnet, Resnet50, Densenet201, Googlenet, and InceptionV3 models. The hybrid model beat the other models in terms of accuracy, getting 97.01%.

Irmak et al. [17] introduced three distinct hybrid models to perform multiclassification of brain tumors while optimizing the CNN models. The first model accuracy was 99.33% which can merely detect brain tumors, The second CNN model, with 92.66% accuracy, can categorize brain cancers into five distinct categories, including normal, glioma, meningioma, pituitary, and metastatic tumors, while the third CNN model, with 98.14% accuracy, can grade brain tumors into Grade II, Grade III, and Grade IV. Performance of the algorithms was assessed by the authors using 4 different datasets. The grid search optimizer adjusts hyper-parameters to create the best CNN model possible.

Kang et al. [18] introduced an approach that uses transfer learning and retrieve deep features from brain magnetic resonance imaging (MR) pictures using a variety of deep convolutional neural networks that have already been trained. In their ensemble module, top three deep features were combined, and utilized as an input to machine learning classifiers. 3 separate publicly accessible brain MRI datasets were used by the authors. It was concluded by the authors that, the DenseNet-169 deep feature performed well for small datasets with 2 classes one is normal and another one is tumor, the ensemble of DenseNet-169, Inception V3, and ResNeXt-50 deep features is a good choice for large MRI datasets with 2 classes, and the ensemble of DenseNet-169, ShuffleNet V2, and MnasNet deep features is a good choice for large MRI datasets with 4 classes (normal, glioma, pituitary tumor, meningioma tumor, and tumor).

A model employing CNN has been developed by Almadhoun et al. [19] to quickly identify brain tumors in MRI images. Along with their suggested model, authors have used and worked with four pre-trained network architectures, including InceptionV3, VGG16, MobileNet, and ResNet. The dataset included 10,000 MRI brain tumor images, of which 5000 showed the tumor and the remaining 5000 did not. The suggested model had 100% training accuracy and 98.28% validation accuracy. Researchers used criteria as training accuracy, validation accuracy, training loss, validation loss, and testing accuracy to evaluate the models. InceptionV3 and VGG16 performed the best in their evaluation, followed by their suggested model. Author's proposed model successfully and accurately identified the presence of a brain tumor.

In Mahbub et al. [20] to quickly identify brain tumors from brain MRI scans, the authors developed a deep neural network-based solution with a tiny number of epochs and parameters. The authors have worked with two datasets in this research work, datasets were taken from “Kaggle”. In order to fit the dimensions of proposed model, the data was preprocessed from 512*512 pixels to 224*224 pixels, and RGB photos were reduced in size to create a greyscale image. The proposed methodology has a validation accuracy of 98.10% and a training accuracy of 100%. Finally, for the first dataset and the second dataset, the suggested model has accuracy of 99.22% and 99.43%, respectively.

For the detection and removal of brain tumors, Qureshi et al. [21] presented an Ultra-Light DL framework for feature extraction and the construction of HFS with textural features, also followed by the method of SVM. Features were extracted by GLCM (Gray Level Co-occurrence Matrix). The suggested model is more fast and more accurate than prior new techniques, requiring just 11.69 ms (detection time per image) to attain an accuracy of 99.23%. Datasets underwent normalization, discrete wavelets-based decomposition, and augmentation during the preprocessing stage. The authors' primary goal was to decrease the detection time, and they were able to do so by 22.07%

by implementing their proposed model Ultra-Light Deep Learning Architecture-based feature extraction.

In [22] Evaluation of 7 pre-trained models demonstrated, including, DenseNet201, VGG-16, InceptionRes- NetV2, ResNet50, InceptionV3 and VGG19 are done by adopting transfer learning technique to retrieve deep-features from MRI of brain images, followed by the utilization of five Machine Learning classifier to classify after extraction. The dataset was subjected to a combination of CNN pretrained models and ML classifiers, and it was found that VGG-19-SVM was the model that performed the best overall, with 99.39% accuracy.

Musallam et al. [23] developed a relatively light-weight model for brain tumor identification, the authors suggested a hybrid architecture with a few convolutional, max-pooling layers and training cycles. Furthermore, they devised a 3-step preprocessing method that entails the elimination of misleading objects, denoising of MRI images, and histogram equalization. Comparing the suggested model to existing new algorithm, it was determined that the suggested model attained an overall accuracy of 97.72%. and needed less computational processing and memory because of the model being lightweight.

2.3 Comparative Analysis and Summary

Based on the information gathered from the reviewed research papers, we discovered that brain tumors are typically diagnosed using MRI scans of the brain. There are additional techniques for detecting brain tumors, such as CT scans and PET CT scans etc. However, MRI is the most popular method due to its low-cost methodology and improved tumor visualization. Previously, traditional human approaches to detecting brain tumors were used, which was a time-consuming and labor-intensive task. The advancement of technology, such as the CAD application to detect disease, has drawn researchers to focus on brain tumor detection through an automated diagnosis process. Deep learning and machine learning are two popular disease diagnosis methods. Deep convolutional networks, on the other hand, have been found to be more successful in brain tumor image recognition. CNN pretrained models are more effective at detecting brain tumors. A few issues we discovered during our investigation include the scientists' struggle with the scarcity of data available for brain tumors. Because the number of people affected by brain tumors is small, there is a scarcity of tumor data. Various algorithms and models are successful in detecting brain tumors, but it is unclear which model is the most accurate in identifying brain tumors.

2.4 Scope of the Problem

A brain tumor is a life-threatening illness that can lead to death. Early discovery may assist in the patient's recovery from disease. Early detection of tumors has become a difficult task when using the traditional approach. Furthermore, the traditional approach is expensive because specialized physicians are required for the task. Which makes it difficult for the patient's family to continue treatment as they have to struggle with the financial condition. Automated detection of brain tumors is a low-cost and simple procedure that is also more accurate than traditional human approaches. As a result, we concentrated on automated diagnosis systems, such as the deep learning approach, to detect brain tumors early. The researchers struggle with a limited amount of data on brain tumors, which we discovered during our review of papers. So, we considered how to solve the problem because deep learning networks provide good accuracy when trained with a large amount of data. We tackled the problem of data scarcity by downloading several MRI images files from the Kaggle repository website and enhancing the images by augmentation. Another issue that we noticed was that there were various CNN architectures used for brain tumor detection, but there was no clear idea about which algorithm was the best in terms of accuracy. We attempted to resolve the issues discovered during the review of the papers. We hope that the methodology we used will aid in the early detection of brain tumors and save patients' lives.

2.5 Challenges

We have faced several difficulties encountered while working on the thesis, but we were able to overcome them. We initially intended to conduct our research using real-world data, collecting brain tumor data from Dhaka clinics and hospitals. When we contacted hospitals, we were told that there were very few cases of brain tumors and that it was not possible to share their resources. So, we decided to continue our investigation using the data that is available online. Then, for data acquisition, we chose the Kaggle repository website. Another issue we encountered when working with Kaggle's raw data. When trained on raw data, the models had very low accuracy. As a result, data processing was required to achieve a high level of accuracy. Because our system configuration did not include a GPU, we needed a longer training time to train the models. Training a single model in the Jupyter lab Python environment took nearly 10 hours and more than that. The models were then trained on the Google Colab platform by connecting the runtime to the local GPU. The code worked properly, but another issue we had with the Colab environment was that the runtime would disconnect after 5-6 hours of running the training process. We were motivated to complete the research at any cost, and we finally tried to maintain our consistency in completing the work by conquering all of the unusual situations.

Chapter 3

Research Methodology

3.1 Research Subject and Instrumentation

In recent years, application of CAD (computer-aided diagnostic tools) in disease detection has advanced significantly. With the blessing of technological advancement, the task of physicians and the medical sector has become easier. Previously, traditional approaches for detecting brain tumors required human intervention. However, detection of brain tumors is not lagging; it has made remarkable progress by utilizing automated tools and techniques. Deep convolutional networks have recently been more successful and improved their ability to identify tumors from MRI images of brain. In order to identify brain tumors, we decided to use CNN architecture pretrained models. We used seven pretrained CNN architecture models, including ordinary CNN, InceptionV3, MobileNetV2, DenseNet201, ResNet50, ResNet101, and VGG19. This work sought to eliminate the shortage of data available for deep learning model training and compare the accuracy obtained by the models. Following the comparative analysis, we are about to evaluate which model is the most accurate in terms of accuracy. The models were put into practice using the programming language of Python. Python libraries and packages such as numpy, pandas, scikit learning, keras, tensorflow were utilized and matplotlib were used for visualization. The Google Colab and Jupyter Lab platforms were the primary research environments for Python code execution.

3.2 Data Collection Procedure/Dataset Utilized

Brain cancer is among the most serious illnesses. Adults and children from around the world are affected by brain tumors. The main objective of this study is to help the medical community identify brain cancers early. To effectively train the models, we needed a massive amount of MRI scans of brain tumors because we were about to use deep learning techniques for our research. We visited a few clinics and hospitals in Dhaka to collect data for this study. However, the hospitals had a negligible amount of data in their collection and refused to share it with us due to patient privacy concerns. As a result, we found that gathering data from hospitals has become more difficult. Then we decided to use data from publicly available online source. We investigated online data repository platforms and discovered two trustworthy sites: "UCI machine learning repository" and "Kaggle". In our investigation we explored the Brain tumor MRI images that are available in Kaggle repository website (publicly accessible). We discovered a good collection of MRI scans of brain tumors. But there was an issue because the datasets were so little in size and were distributed in several files. We used a merging mechanism to gather data from Kaggle since deep learning algorithms perform better when trained on huge amounts of data. Therefore, we made the decision to merge the datasets to increase data volume. A dataset of 10,000 MRI pictures was produced by merging several separate brain MRI datasets that were downloaded from Kaggle. The images are arranged in two folders with the labels "Yes" and "No," with “Yes” denoting images of the brain with tumors and “No” denoting images of the brain without tumors.

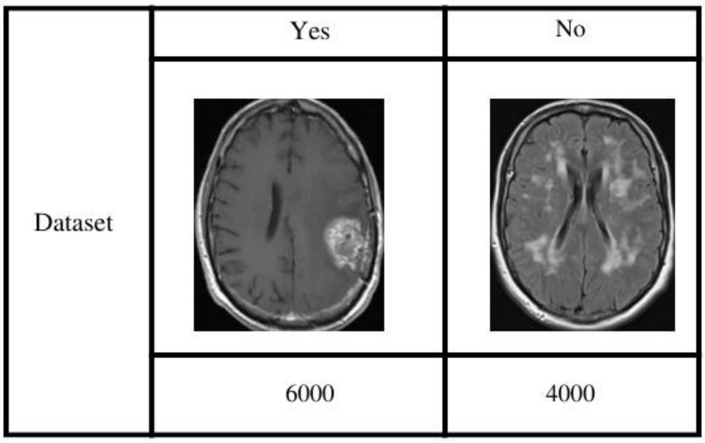

Figure 3.1: Description of the dataset.

The following Figure 3.1 describes about the dataset that we have used in our research. “6,000” images with tumors were abnormal and were arranged in the folder "Yes," while “4,000” images were healthy without tumor were arranged in the folder "No". The images were in JPG format and were in grayscale.

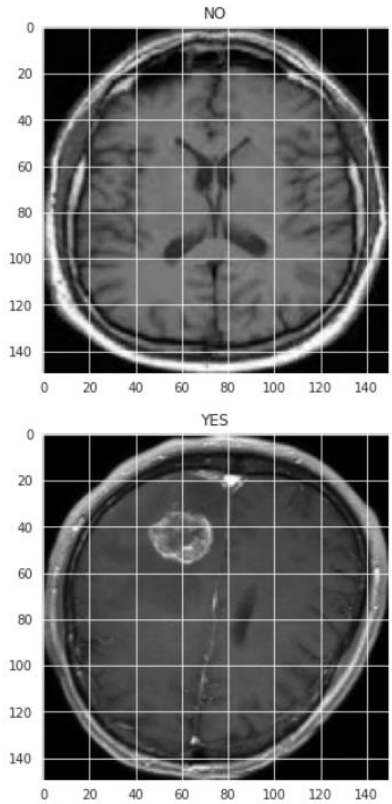

Figure 3.2: Visualization of the 2D grayscale images taken from our dataset.

2D visualization of the images under the labels “Yes” and “No” are demonstrated in the Figure 3.2. The image under “No” is clearly showing that there is no presence of tumor in the MRI scan. While the image under “Yes” is defining that the MRI scan of brain contains tumor which is the abnormal condition of the brain.

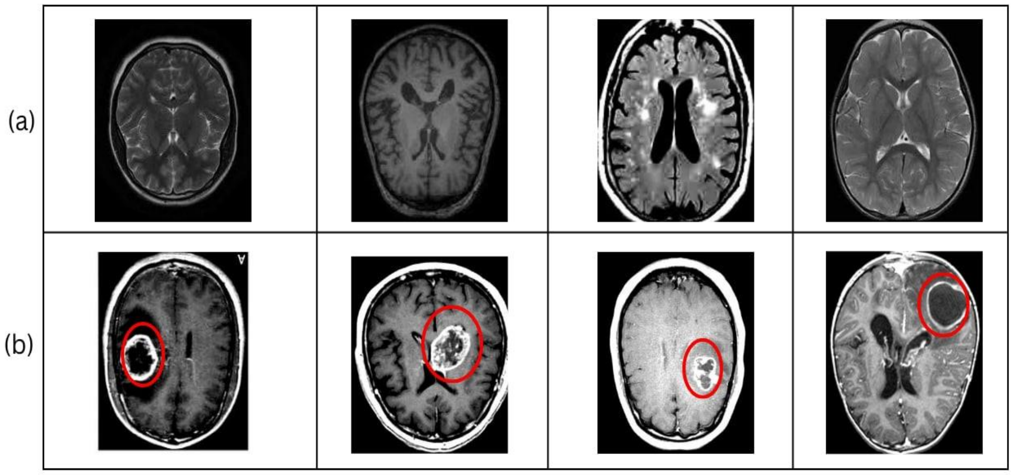

Figure 3.3: (a) is the sample figure of brain MRI images without tumor, (b) is the sample figure of brain MRI images with tumor(marked).

A clear demonstration of the sample photos of the 2 categories: tumor and without tumor—has been generated in Figure 3.3 using a small number of photographs from the original dataset. Figure 3.3(a) shows about some sample images of brain which are healthy and not having tumor in the brain. Figure 3.3(b) shows about the sample images that are already affected by tumor and the presence of tumor is visible in the scan. For better simulation of the figures, the tumor affected area is red circle marked.

3.3 Statistical Analysis

The dataset of 10,000 MRI images that we have created for our particular research is picked from the publicly accessible data repository platform "Kaggle". We looked through the website "Kaggle" for information about brain tumors. We discovered several brain tumor datasets with two image classes (with tumor and without tumor). All datasets with two classes were gathered and merged to form a single dataset. We were able to create a dataset of 10,000 images after merging the datasets and classifying them into two categories ("Yes"," "No"). So, the original dataset for our study contained 10,000 quantities of brain MRI images, with 6,000 images containing tumor and 4,000 images containing no tumor. Images with tumors were organized in the "Yes" folder, while images without tumors were organized in the "No" folder. The two classifications and the number of images under each class are represented in a bar graph in Figure 3.4.

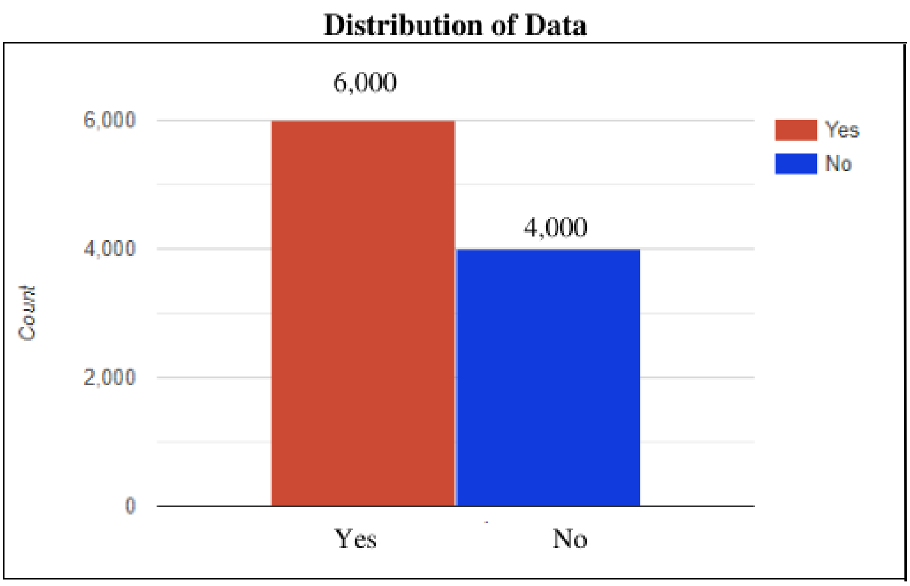

Figure 3.4: Bar chart representation of the distribution of Brain MRI images in two classes.

3.4 Proposed Methodology/Applied Mechanism

Our proposed methodology includes collecting the dataset, augmenting the data, preprocessing the data, training pretrained CNN models with enhanced dataset, demonstrating comparative model accuracy, and recommending the most effective model for detecting brain tumors.

In order to help CNN models accurately detect brain cancers, data augmentation and processing of image techniques were used in this study using a dataset of 10,000 brain tumor MRI images. Because building a CNN model entirely from scratch takes a lot of time and effort, we decided to employ pre-trained models for our research. Regular CNN, InceptionV3, MobileNetV2, DenseNet201, ResNet50, ResNet101, and VGG19 were among the seven pretrained CNN models that we employed. Training, Validation, and Testing folders were the partitions made upon our augmented dataset. While the images in training were used for model learning, the validation data is applied to model evaluation and parameter adjustment. Ultimately, our models will be assessed using the test data. The most effective model for detecting tumors of brain from MRI input data was determined after a comparison of the models' performances.

The following Figure 3.5 describes about the visual representation of the overall workflow of our followed approach for the research.

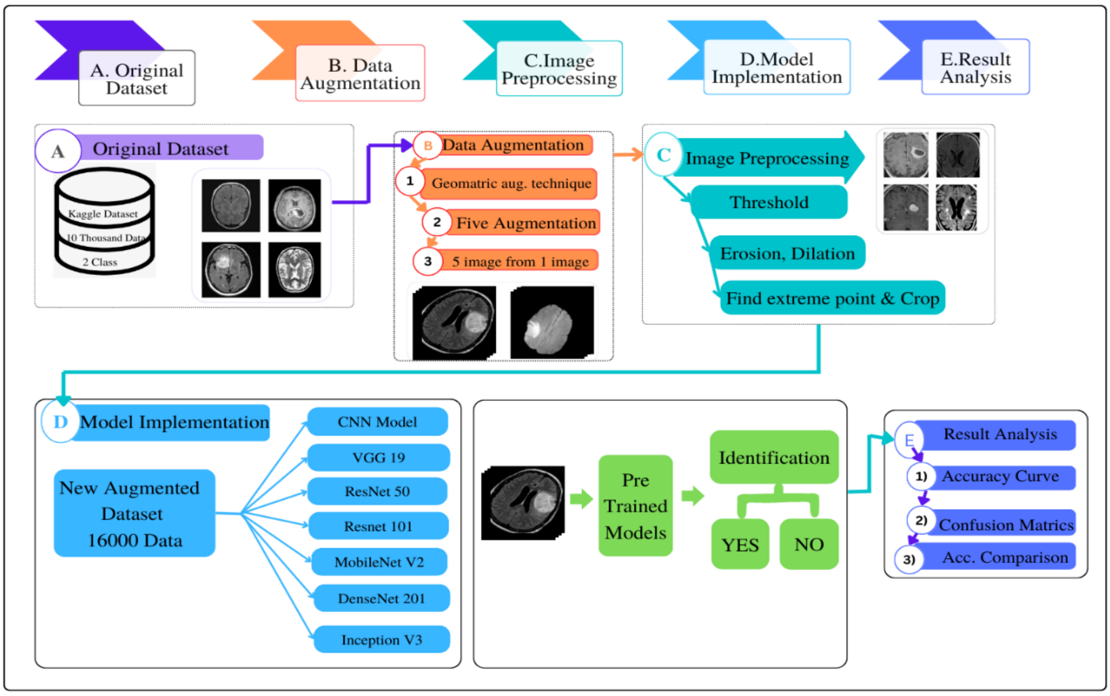

Figure 3.5: The entire workflow of our research work.

3.4.1 Data Preprocessing

Preprocessing of data is an essential step in image processing. It is an important step in reaching the goal. We can indeed improve the quality and clarity of an image by performing certain activities on it prior to further processing. Depending on the nature of image and the desired results, a variety of preprocessing techniques can be used. Before the MRI images are fed into the deep learning models, they are preprocessed.

3.4.2 Data Augmentation

Researchers have become interested in deep learning approaches as a result of recent developments in the area of medical image diagnosis. In many types of diagnosis based on medical imaging, like the tumor of brain, lungs cancers, breast cancers, malignancies related to skin and many more. DL networks are commonly employed. In particular, CNN's pretrained models are excelling in this field by accurately identifying diseases from medical images. However, a problem is emerging as a result of the dearth of diseased imaging data. Since the diseases indicated is not one that affect the greatest number of people, there are so few data regarding diseased images. Data augmentation is a useful tool in this case because DL algorithms struggle with little data. Making copies or duplicates of already-existing data by making minimal modifications to them is known as data augmentation. The robustness of models will be ensured, and overfitting will be avoided, by producing more data through image augmentation. Five augmentation techniques were used in this study: rotation, height shift, width shift, vertical flip, and shearing. The Figure 3.6 below demonstrate the augmentation process.

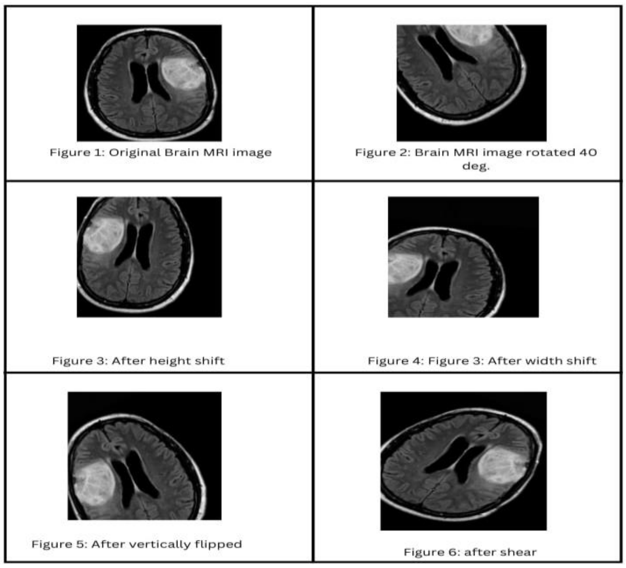

Figure 3.6: Data augmentation process (rotation, height shift, width shift, vertical flip, and shearing).

After performing augmentation, the dataset volume was raised to 16,000 images from 10,000 images. Figure 3.7 below shows the amount of data under the label “Yes” and “No” after the augmentation is performed.

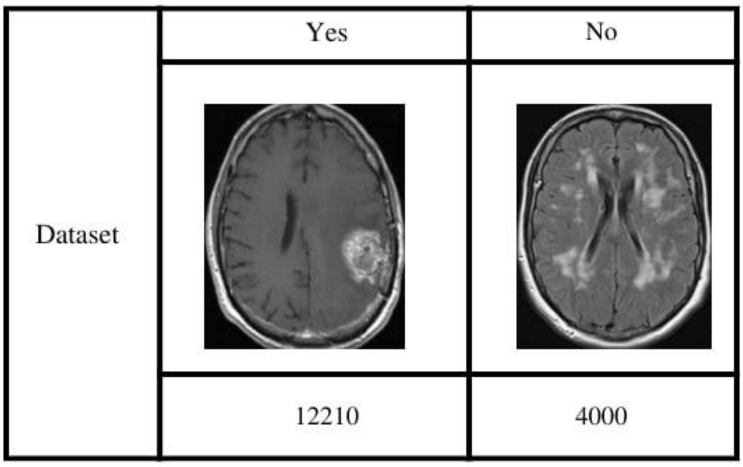

Figure 3.7: Description of the augmented dataset.

3.4.3 Image processing

The brain tumor images in the dataset were preprocessed by resizing them into target size. For a large size of image there will be an increase in computational processing time for training the models. The images were including some extra portions that were not required for tumor identification. So, these unwanted portions were removed by cropping the images and focusing on the useful part only that is brain. The image preprocessing technique was applied to the augmented dataset of 16,000 images. Processed and cropped images are split and stored into three folders: “TRAIN”, “TEST” and “VAL”.

The image pre-processing stage in this study includes a number of steps. In the first step, the actual MRI images of grayscale color of different size from the dataset were imported for the preprocessing.

The image data are done thresholding in second step. Image thresholding is a simplistic type of image segmentation. It is a method for converting a grayscale or full-color image to a binary image.

The third step involves erosion and dilation. Erosion and dilation are fundamental geometrical processing operations that yield diverse outcomes when implemented on grayscale or binary pictures.

The image contouring procedure is then carried out as the next step. Using contour detection, we can easily detect the borders of the brain and localize its position in an image. Following that, extreme points are chosen and the images are cropped on the basis of contouring and extreme points.

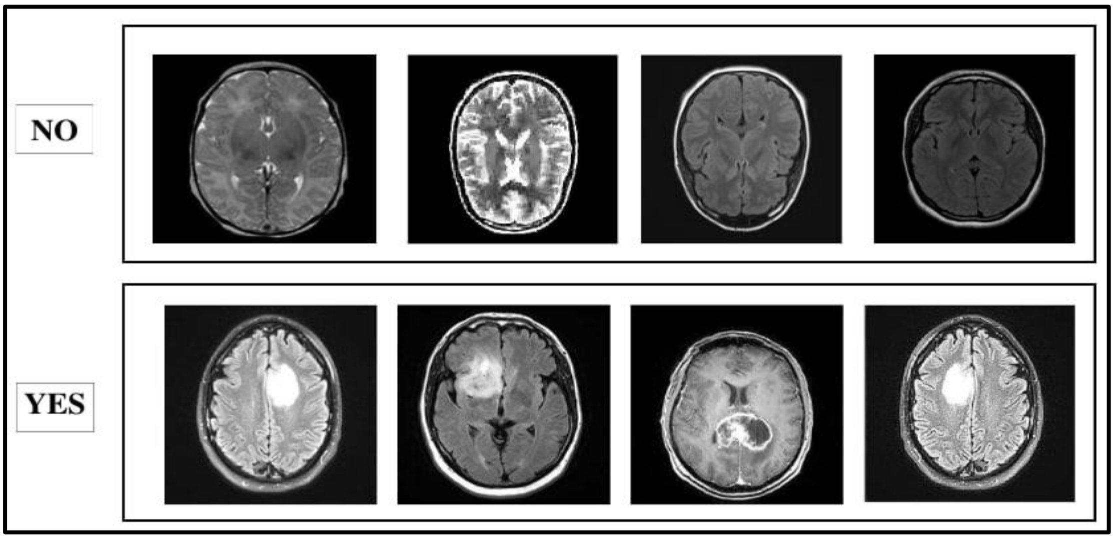

Figure 3.8: Raw MRI images before cropping.

Figure 3.8 is the visualization of the raw images taken from the augmented dataset when no processing of images was performed.

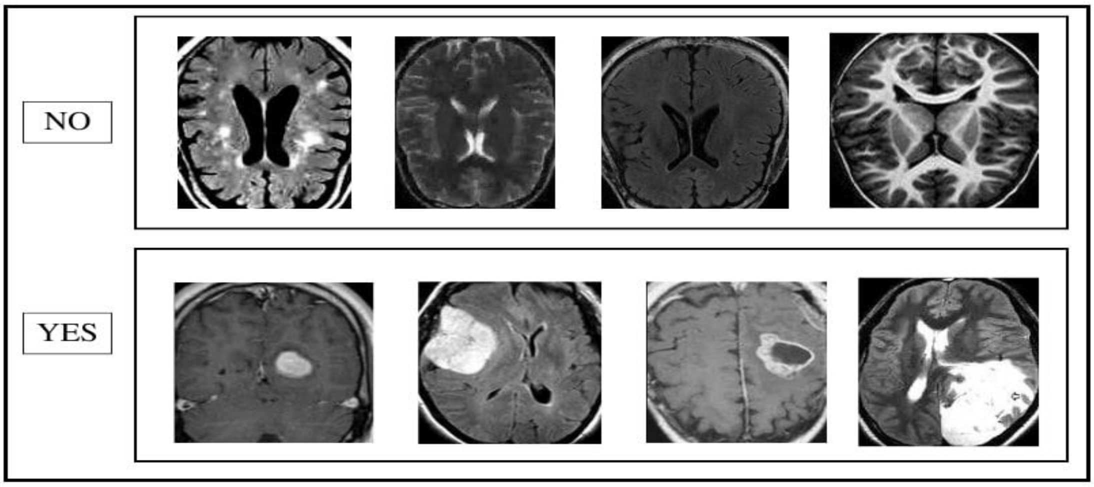

Figure 3.9: MRI images after cropping.

In Figure 3.9 the images demonstrated are found after performing the image processing techniques. The images of the two classes "Yes" and "No" both of them were processed.

3.4.4 CNN (Convolutional Neural Network)

Convolutional neural networks, which analyze data in a matrix form, are extensively used feed-forward neural network models to evaluate visual pictures. CNNs are also recognized as ConvNet. Convolutional neural networks are employed to identify and categorize objects in images [24]. It is a powerful network which extract features from photos using filters. As compared with traditional feed-forwarding neural networks, the architecture of the CNN is developed from the idea of the neurons present in the brain, enabling it to extract important information from images [25]. Some of the capable of learning filters (or kernels) that keep a limited range area but improve it throughout the depth of the input density are included in the layer parameters [26]. The Figure 3.10 is a visual representation of the architecture of CNN.

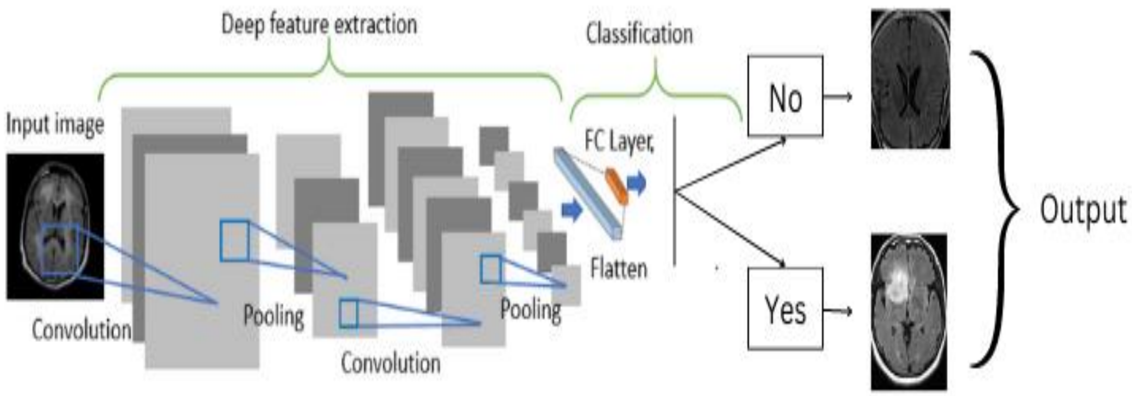

Figure 3.10: Architecture of the CNN model.

CNN is widely applicable for the classification of images, recognition of image, segmentation and many other things. Since CNN has advanced to recent image recognition, we choose it to identify brain tumors in this study. Classification of the data and extraction of features are CNN's two primary components. Pooling and convolution layers are employed in feature extraction, whilst a fully connected layer is used in classification [25].

3.4.4.1 Convolutional layers

A convolutional layer is regularly the very first layer of a CNN model. Before sending the output to the subsequent layer, convolutional layers execute a convolution operation on the data. All of the particles in a convolution's visual field are combined into a single fixed dimension. The 2D convolution layer, commonly known as conv2D, is the most common type of convolution layer. In case of a 2D convolutional layer, filter and kernels refers the same entity which perform a sliding operation through the two-dimensional inputs to conduct multiplication of the elements. In reality, the outcomes are merged to create a single output pixel. Every time it moves over a point, the kernel will carry out the identical action, changing one 2D feature matrix into another [27].

3.4.4.2 ReLU

ReLU stands for rectified linear activation unit. An important key turning points in the deep learning trend is the (ReLU). It's indeed simplistic yet vastly superior than earlier activation mechanisms like the tanh or sigmoid [26]. ReLU is a non-linear or piece -wise function that, if the input is positive, returns the value directly; if not, it returns 0. Though it acts like a linear function. It is, however, a non-linear function which is required in order to pick up and learn complex relationships from training data. ReLU increases the sensitivity of the weighted sum, preventing neurons from becoming saturated [28].

3.4.4.3 Pooling Layer

By pooling layers, the dimensions of the feature maps are decreased. It thus decreases the quantity of computation carried out within the networks as well as, the amount of parameters to learn [29]. The primary function of the pooling layer is to lessen the complications of the layers that comes in the next. Maximum pooling, average pooling, and sum pooling are the 3 different kinds of pooling. Nevertheless, pooling seems to have no impact on the quantity of filters. The convolutional layer produces a high amount of features for each picture. During the training phase, these characteristics may cause overfitting. Maximum pooling is used to avoid overfitting by selecting the feature map with the highest value [26]. Since the features' positions in the input data can change, but the model is therefore more resilient to such changes.

3.4.4.4 Fully Connected Layer

In neural networks, fully-connected layers, sometimes referred to as linear layers, establish a link or connection of the input neurons with the output neurons. Fully linked layers in a neural network are those where each of the inputs from 1 layer are connected to each activation unit of the following layer. Most common machine learning models have a final set of fully linked layers that combine the input retrieved by earlier levels to create the final output. And after Convolution Layer, it takes the second-longest time [30].

3.4.4.5 Softmax

A vector of “K” true numbers is transformed into a vector of “K” true numbers that aggregate to one by the softmax function. Input parameters which are negative (-), positive (+), zero (0), or higher than 1 are converted by the softmax into values within 0 and 1, which enables them to be perceived as likelihood. The softmax transforms inputs that are little or negatives into minor possibilities; inputs that are high are transformed into big likelihoods; however, the likelihoods have always been within zero and one.

3.4.5 Pretrained CNN architectures

A pre-trained model is one that has already been created and received training by someone else to solve an issue related to ours. There are a large number of models available online that are based on the architecture of CNN and were developed by anyone else by training them with larger datasets. The pretrained model's key benefit is it does not require to be trained or built from scratch. We will use some pretrained models in our research because it takes a lot of effort and time to train a new model from the beginning.

3.4.5.1 Introduction to InceptionV3

Inception is the variety of pretrained CNN network architecture which is also recognized as the GoogleNet,and it was developed by Google in the year 2014. Initially, there were 22 layers and 5M parameters in the inception network, filter sizes of 1x1, 3x3, and 5x5, and max pooling to retrieve information at many scales. The reason for using 1x1 filters is to save computation time. Then in the year 2015, Google upgraded the Inception model's fidelity to InceptionV3 (48 layers deep), factorizing the Convolutional layers to minimize parameters. To reduce computation while preserving network performance, two 3x3 filters were used in place of 5x5 Convolutional filters [7]. Convolutions, max pooling, average pooling, concatenations, fully connected layers and dropouts are all part of the Inception V3 model, which uses the batch normalization to activate inputs and the Softmax to compute the Loss [32]. The following Figure 3.11 depicts the architecture of InceptionV3 model.

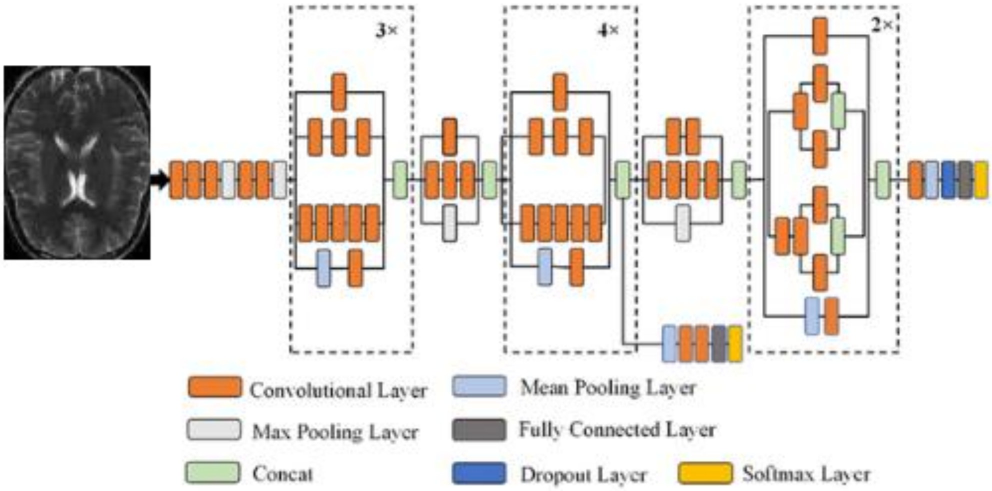

Figure 3.11: Architecture of InceptionV3.

3.4.5.2 Introduction to MobileNetV2

The architecture of MobileNetV2 is based on the design of residual framework, with the residual block's input and output being narrow bottleneck layers. Though the traditional residual architectures use expanded presentation of input and output, MobileNetV2 is different from these. MobileNetV2 uses compact depthwise convolutions to filter features in the middle expanding layer. In comparison to the first MobileNet, it contains much less parameters. Every image's pixel value greater than 32×32 can be handled by MobileNets, and higher pixel sizes of images offer competitive advantage [33]. In MobileNetV2, there are 2 different types of blocks. Residual block having a stride of one will be comprising the first block of MobileNetV2.A block having a stride of two is the additional choice for shrinking. The blocks contain three levels for both types. This time, the very 1st layer is a 1 x 1 convolution with ReLU6. The 2nd layer is the depthwise convolution. Another 1 x 1 convolution is used in the third layer, however this time there isn't any non-linearity [34]. The model MobileNetV2's architecture is shown in Figure 3.12.

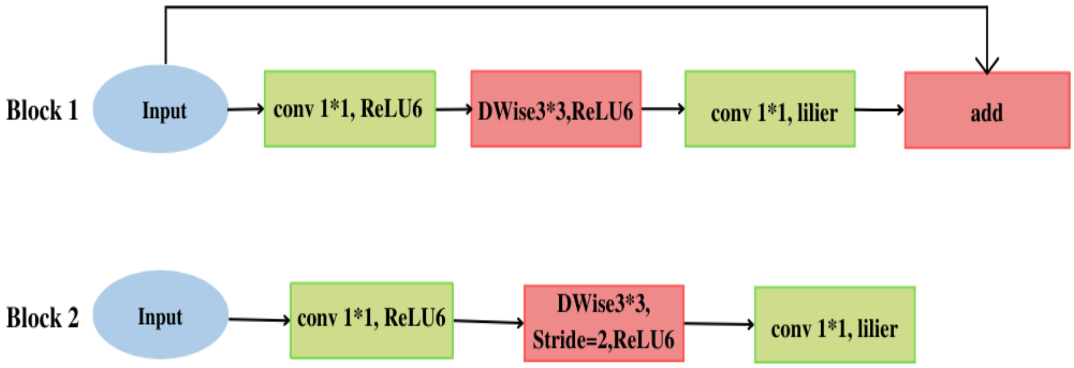

Figure 3.12: Architecture of MobileNetV2.

3.4.5.3 Introduction to DenseNet201

Huang et al. [35] proposed DenseNet, which is known for its impressive performance on 4 benchmark datasets for object recognition, including CIFAR-100 and ImageNet [36]. DenseNet provides integration of all feature maps from earlier levels to ensure maximum information exchange across network layers. This ensures that the all-feature maps propagate to subsequent layers and are linked to freshly created feature maps. With this architecture, DenseNet offers a number of outstanding benefits, such as lessening the problem of vanishing gradients, enhancing feature transmission, enabling retouching, and significantly lowering the amount of parameters [35]. 3 transition layers and 4 dense blocks are included in DenseNet architecture design. Dense blocks employ convolution kernels with 1 x 1 and 3 x 3 matrix sizes. Convolution kernels throughout DenseNet's dense blocks repeat 6, 12, 24, and six times. In this architectural model, there is a transition layer in between dense layer. A dense block's individual feature extractor convolution layers are all feedforward coupled to one another. The transition layer of the DenseNet architecture is composed of convolution, batch normalization, and pooling layers with kernel sized 1 x 1. The pooling layer has a 2x2 stride [37]. A pictorial representation describing the architecture of the DenseNet201 is provided in Figure 3.13.

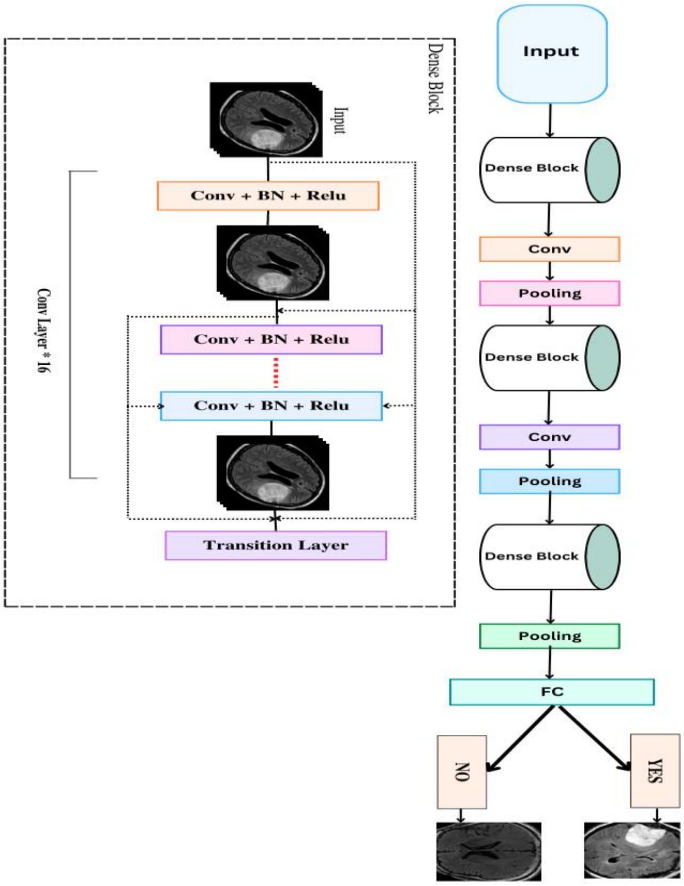

Figure 3.13: Architecture of the DenseNet201.

3.4.5.4 Introduction to ResNet50

ResNet50 is a 50-layers Residual Network and 26M parameters. The residual network, a deep convolutional neural network model, was introduced by Microsoft, in 2015 [38]. This is the first neural network capable of training hundreds or thousands of layers while avoiding the issue of "vanishing gradient" [19]. 'ResNets' Residual Networks are networks with pooling, convolutional, activation, and fc (fully connected) layers. Convolutional and identity blocks, which link up the result of one layer with the input of a previous layer, are the fundamental building blocks for ResNets [32]. The architecture of ResNet-50 is separated into five stages. For initial convolution and max-pooling, each ResNet architecture employs 7 x 7 and 3 x 3 kernel sizes, respectively. Every convolution block has three convolution layers, and every identity block has three convolution layers. There is also a fully - connected layers with 1000 neurons and an Average Pooling layer in the network. The Figure 3.14 is represented below for the visualization of the architectural view of ResNet50.

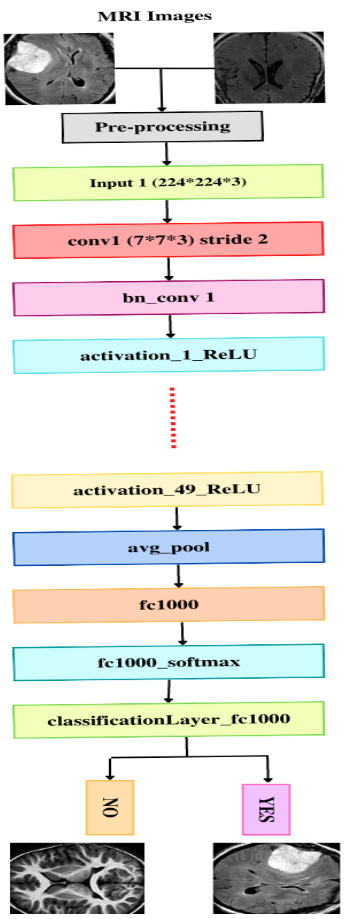

Figure 3.14: Architecture of the model ResNet50.

3.4.5.5 Introduction to ResNet101

ResNet (Residual Networks) makes an important statement concerning computer vision challenges. The ResNet network includes residual connections via which gradients can flow directly to prevent gradients from reaching zero after applying the chain rule.

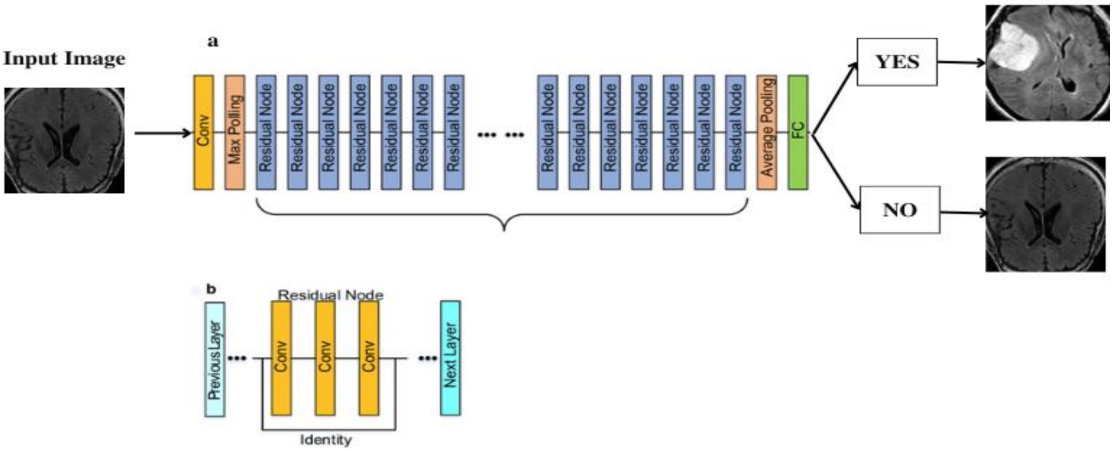

Figure 3.15: Architecture of the ResNet101 model.

The model ResNet101 architecture is illustrated in the Figure 3.15 to know better about the structure of the model.

ResNet-101 includes 104 convolutional layers in total. [39]. Furthermore, it has 33 layers in all, with 29 of these blocks utilized the previous block's output directly, as shown by the remaining connections above and these residuals serve as the first operand of the summing operator. To get the input of the following blocks, summation operator is used along end of each block [38]. Four resting blocks are use the result of the previous block in a convolution layer which have a filter size of 1x1 and a stride of 1, relieved by a normalization batch layer which accomplishes normalization processes, as well as the resultant result go on delivered toward summation operator at that block's result [39].

3.4.5.6 Introduction to VGG19

VGGnet is an abbreviation for visual geometry group network, which is a multilayered deep neural network. Simonyan et al [43] proposed VGG19 in the year 2014 from the University of Oxford. VGGNet is created using the CNN paradigm. VGG-19 is advantageous due to its simplification, with 3 x 3 convolutional layers placed on top to improve with depth level. In VGG-19, max pooling layers were utilized as a handler to reduce size of volume. With 4096 neurons, two Fully Connected layers were used [41].

VGG-19 based on Convolutional Neural Network architecture is said to produce great accuracy when handling massive data like ImageNet. The model of VGG-19 contains approximately 143 million of parameters, which are derived from the ImageNet dataset, which contains 1.2 million common target images from 1,000 various target classification because of training [42].

The Figure 3.16 will help to understand the architecture of the model by demonstrating the structural formation of the layers of the model VGG19.

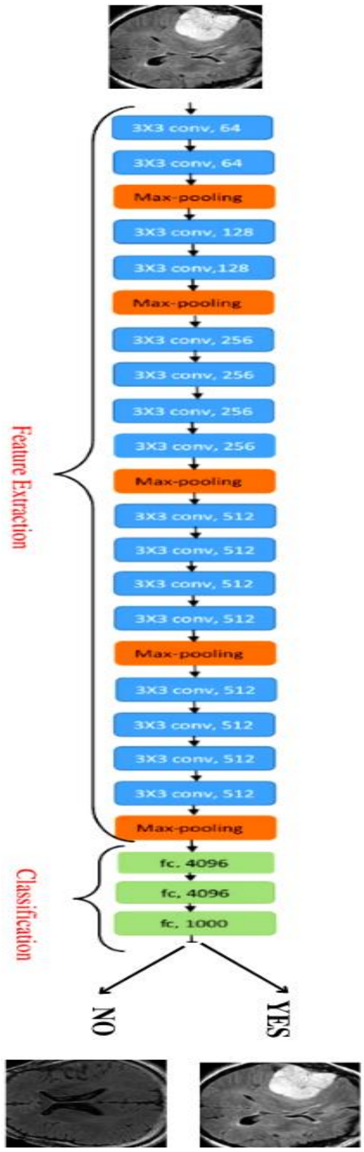

Figure 3.16: Architecture of the model VGG19.

3.5 Implementation Requirements

Deep learning model implementation necessitates a highly configured computer setup in order for computational codes to run smoothly and training time to be reduced. The addition of a GPU to the system can improve training performance. Since our system configuration did not include a GPU, we were forced to spend more time training the models. We believe that if GPU were added to our system, the models we investigated in this study could be trained much faster. Despite the fact that the training of the models took many hours, we were successful. The requirements we used for this research are listed below.

Used system specifications are:

Hardware:

- Intel(R) Core (TM) i5-9400 processor,
- CPU base clock 2.90 GHz, boosted to 4.10 GHz,
- 8 GB DDR4 RAM,
- 128 GB SSD,
- 1 TB HDD,
- Input Output devices (Mouse, Keyboard etc.),
- Integrated iGPU of Intel Processor.

Software:

- Operating system (Windows 10 Pro),
- Anaconda Navigator,
- Canva image editor.

Development platforms:

- Python integrated environment,
- Jupyter Lab,
- Google Colab.

Chapter 4

Experimental Results and Discussion

4.1 Experimental Setup

We have used the libraries of TensorFlow 2.0, keras 2.11.0 and a programming language Python 3.10.4 to implement and test the proposed models. For model implementation, we used the environments Jupyter notebook and Google Colab. We have also used the seaborn and matplotlib libraries for visualization. An Intel(R) Core (TM) i5 processor running at 2.90 GHz, 8GB of RAM, an iGPU, and Windows 10 were included in system specification

4.2 Experimental Results & Analysis

The purpose of this study was to identify brain tumors from images of brain MRI scans. Different pretrained deep learning models were used for identification, and their individual performance for detecting brain tumors was compared. This study's data set was obtained from an open-source data repository. We obtained several data files containing Brain tumor MRI data from the open data platform "Kaggle." The several data files were merged together to form a single dataset, which contained 10,000 image of Brain MRI scans. Out of the 10,000 images 6,000 images were with tumor(unhealthy) that were labelled under the folder “Yes” and there was another label named “No” which contained 4,000 images of brain without tumor(healthy). The dataset was then augmented and preprocessed to enhance the amount and quality of data. In our research augmentation technique followed the process of rotation, height shift, width shift, vertical flip, and shearing to generate 5 images from an input of single image. Augmentation was applied on the image of tumor only. We created an augmented image dataset of 16,000 images (12,210 images with tumor and 4,000 images without tumor). We divided our augmented dataset into three parts: training, testing, and validation. There are 12,358 training images, 3,239 validation images, and 600 testing images to determine the accuracy of our model. We increased the amount of data in the training portion, as we know that the deep learning models performs better if they are trained with large amount of data.

On the same dataset, seven pretrained models were implemented to compare their accuracy in detecting brain tumors. A batch which size is 32, we trained all the models for 20 epochs except the CNN, CNN were trained on 12 epochs. By using an optimizer named “Adam”, we have trained the models, ReLU and Softmax were used as activation functions and as a loss-functions we have used categorical cross entropy. After augmenting the data and preprocessing them, the data were implemented on the seven pretrained models and the accuracy we obtained were like CNN had 98.17%, InceptionV3 got 96.8%, MobileNetV2 got 97.6%, DenseNet201 got 99%, ResNet50 got 79%, VGG19 got 98.95%, ResNet101 got 98.6%. These models were trained on the 12,358 images data that were under the folder “training” and validated on 3,239 images data that were under folder “validation”. The following figures provide accuracy graph of training and validation of the seven models.

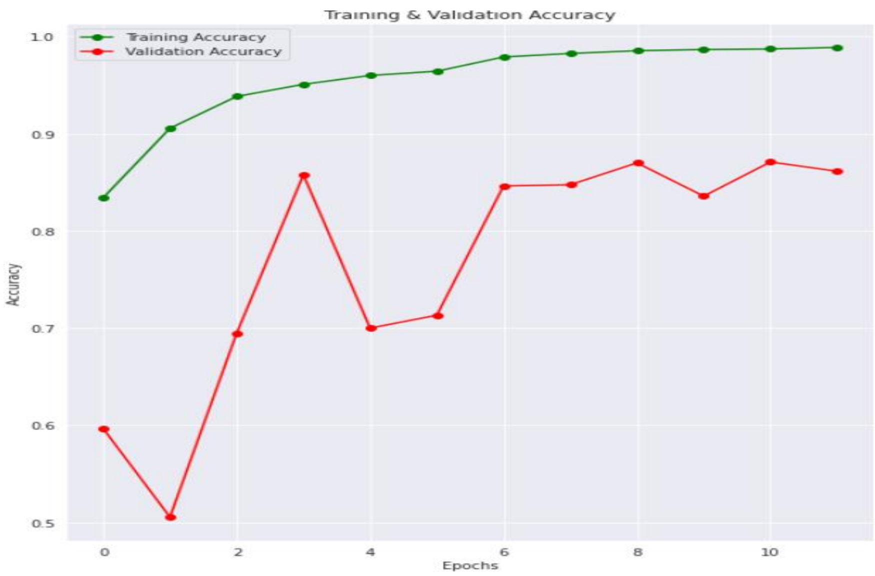

Figure 4.1: Accuracy curve of the graph showing training and validation accuracy of CNN.

Figure 4.1 illustrates that while implementing the CNN model on our dataset, we obtained training accuracy of 98.88% and when the model was done validation it obtained 86.14% of accuracy.

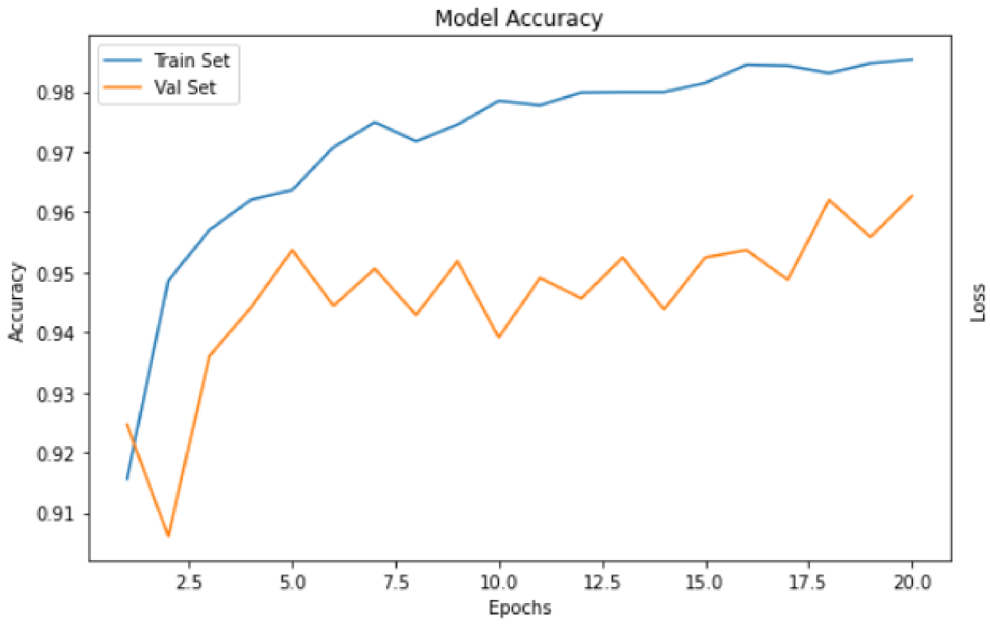

Figure 4.2: Accuracy curve of the graph showing training and validation accuracy of InceptionV3.

In Figure 4.2, it is demonstrated that the model InceptionV3 has got 98.54% of training accuracy and 96.26% of validation accuracy.

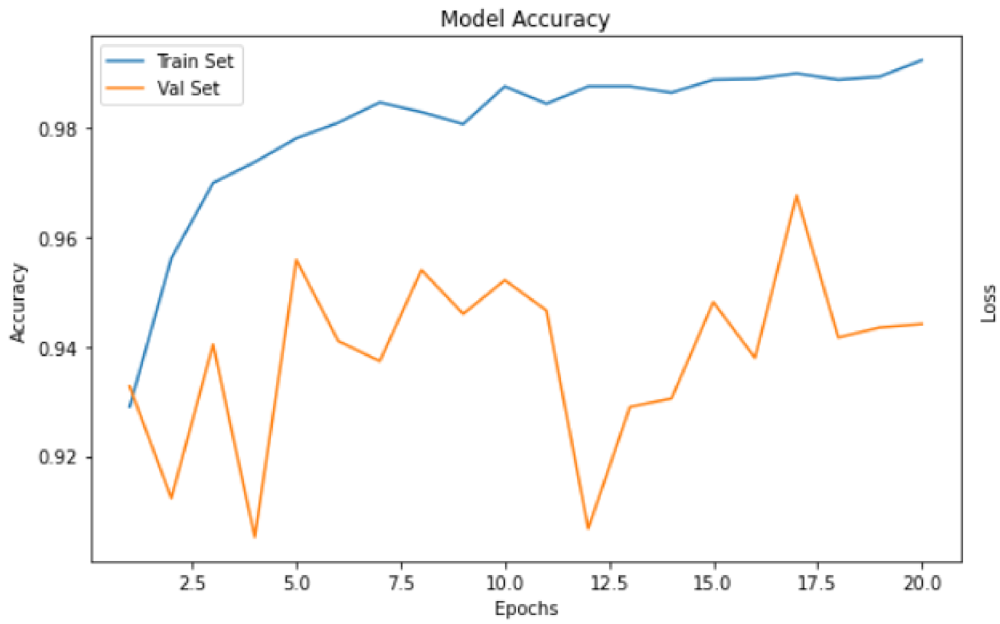

Figure 4.3: Accuracy curve of the graph showing training and validation accuracy of MobileNetV2.

Figure 4.3 shows that, MobileNetV2 model achieved 99.23% training accuracy and 94.41% validation accuracy.

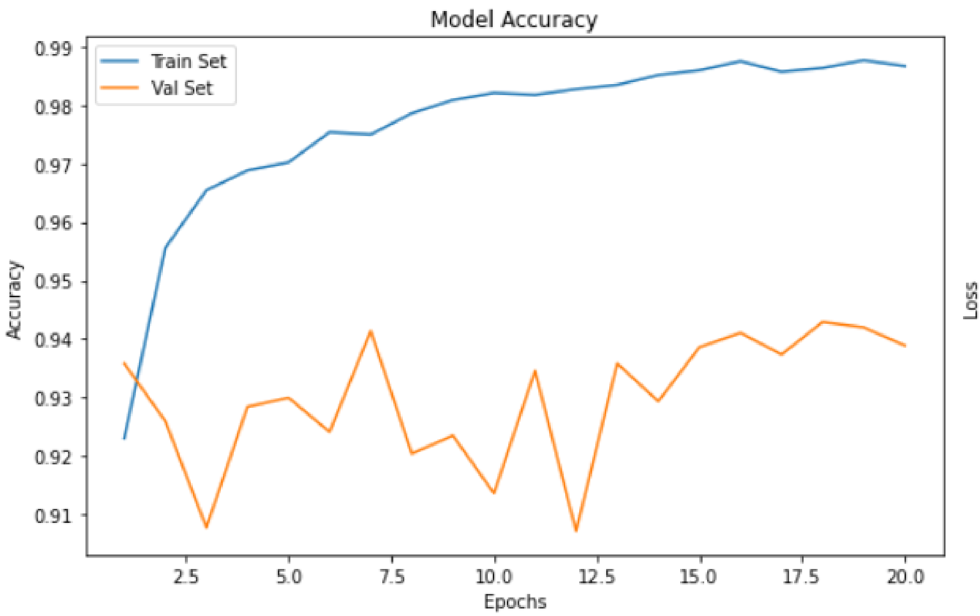

Figure 4.4: Accuracy curve of the graph showing training and validation accuracy of DenseNet201.

Figure 4.4 demonstrates that, DenseNet201 model has 98.67% of training accuracy and a 93.89% of validation accuracy.

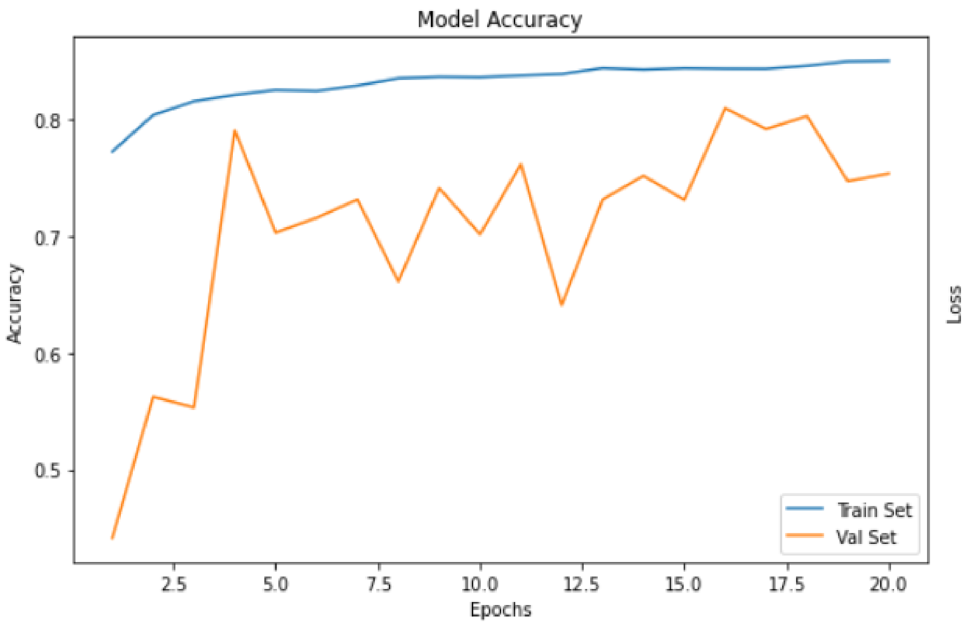

Figure 4.5: Accuracy curve of the graph showing training and validation accuracy of ResNet50.

In Figure 4.5, it is demonstrated that the model ResNet50 has got 85.07% of training accuracy and 75.39% of validation accuracy.

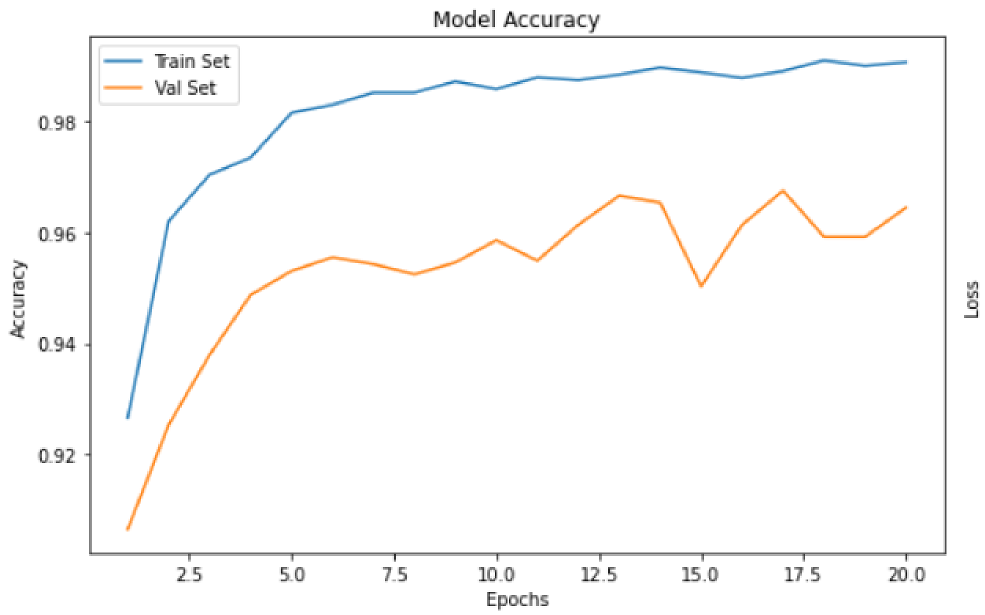

Figure 4.6: Accuracy curve of the graph showing training and validation accuracy of ResNet101.

Figure 4.6 reveals that, ResNet101 model has 99.08% of training accuracy and 96.45% of validation accuracy.

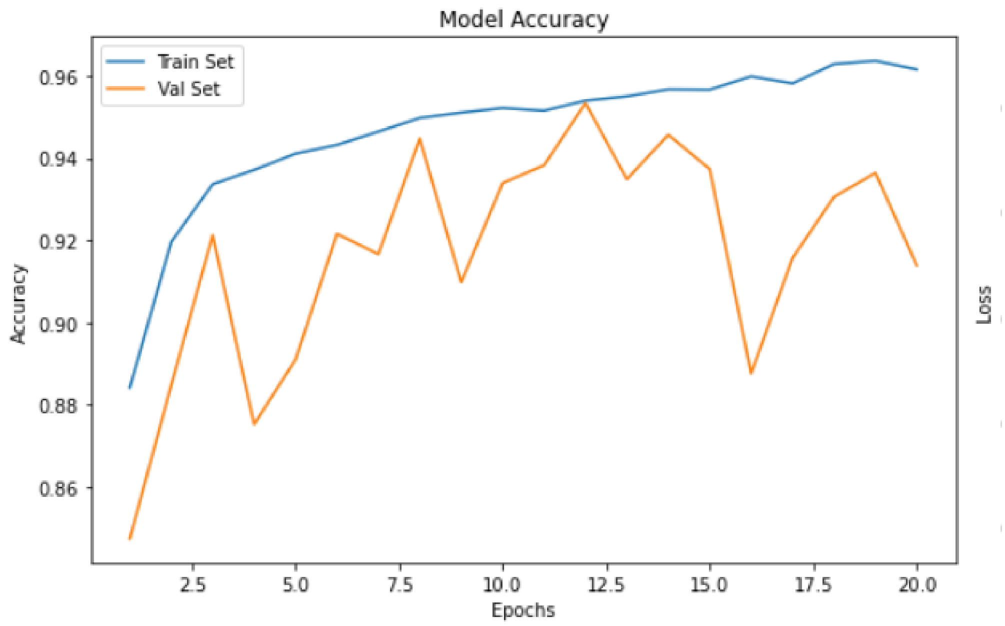

Figure 4.7: Accuracy curve of the graph showing training and validation accuracy of VGG19.

In Figure 4.7, it is demonstrated that the model VGG19 has got 96.16% training accuracy and 91.39% validation accuracy.

Evaluation metrices: This section will describe the performance measures being used to quantify the models' identification performance. There are various ways to assess the effectiveness of the models, but we validated the results using a confusion matrix-based measurement. Performance indicators like as accuracy, precision, recall, and F1-score are used to assess the diagnostic power of the models.

Accuracy: The capacity to correctly detect a brain tumor from a specified picture dataset is characterized as accuracy/correctness. The proportion of true positive and true negative in all instances under investigation is used to measure accuracy:

$$\text{Accuracy} = \frac{\text{Truepositive(TP)+TrueNegative(TN)}}{\text{Total Number of Sample(TP+FP+TN+FN)}} \ldots\ldots\ldots\ldots\ldots (1)$$

Precision: Precision is a true positive sign, suggesting that the model classified the images accurately as positive. It's computed as follows:

$$\text{Precision} = \frac{\text{TruePositive(TP)}}{\text{TruePositive(TP)+FalsePositive(FP)}} \ldots\ldots\ldots\ldots\ldots (2)$$

Recall (Sensitivity): Recall is a metric that gauges the system's capacity to precisely identify brain tumors. It is used to detect patients who have a brain tumor. The formula for recall is:

$$\text{Recall} = \frac{\text{TruePositive(TP)}}{\text{TruePositive(TP)+FalseNegative(FN)}} \ldots\ldots\ldots\ldots\ldots (3)$$

F1-score: The harmonic mean of recall and precision is used to get the F1-score. F1-score is determined by:

$$\text{F1} - \text{score} = 2 \times \frac{(\text{Recall}\times\text{Precision})}{(\text{Recall+Precision})} = \frac{\text{TruePositive(TP)}}{\text{TruePositive(TP)}+{}^{1}/_{2}\,(FalsePositive(FP)+FalseNegative(FN))} \ldots\ldots\ldots\ldots\ldots (4)$$

To evaluate these metrics, we had to calculate the true positive, false negative, true negative, and false positive values.

TP: The count of images accurately identified as the patient of brain tumor.

FN: The count of pictures that were incorrectly classified as good.

FP: The count of pictures incorrectly labelled as the patients of brain tumor.

TN: The count of pictures that were accurately identified the brain as healthy.

Total number images used for testing were 600 (300 image for both "Yes" and "No"). When the models were tested, they provided confusion matrix to provide information about the False Negative, False Positive, True Negative, True Positive values of identification from test data. The following Table 4.1 demonstrate the identification performance of the seven models.

Table 4.1: Identification performance of the model based on confusion matrix.

Algorithms	**Predict** → **Actual** ↓	NO	YES
CNN	NO	2	298
	YES	295	5
InceptionV3	NO	292	8
	YES	11	289
MobileNetV2	NO	295	5
	YES	9	291
DenseNet201	NO	298	2
	YES	4	296
ResNet50	NO	0	300
	YES	176	124
VGG19	NO	294	6
	YES	0	300
ResNet101	NO	292	8
	YES	0	300

The following figures represent the visualization of the confusion matrix of the seven models that we have implemented in our research.

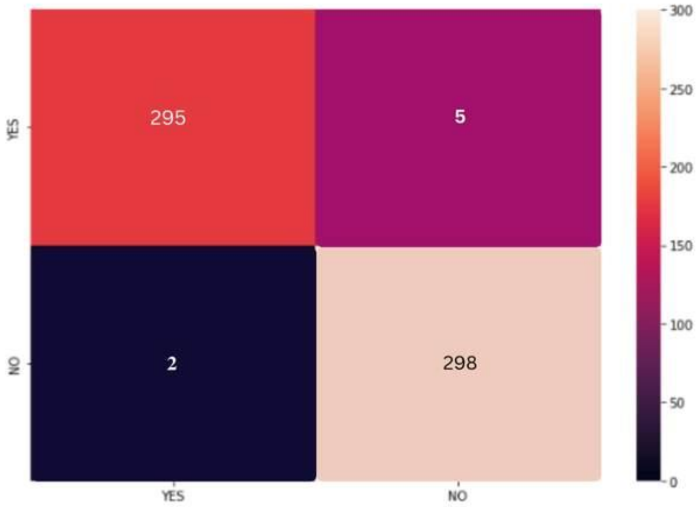

Figure 4.8: Confusion matrix of CNN.

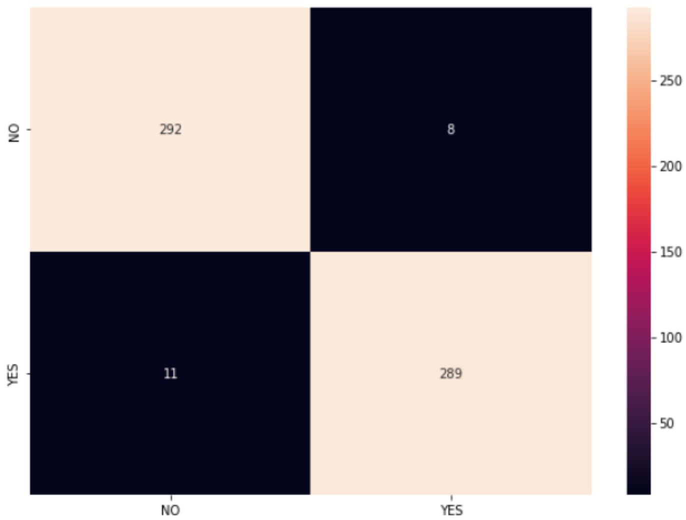

Figure 4.9: Confusion matrix of InceptionV3.

Figure 4.8 and Figure 4.9 are the demonstration of the confusion matrices of CNN and InceptionV3 models respectively.

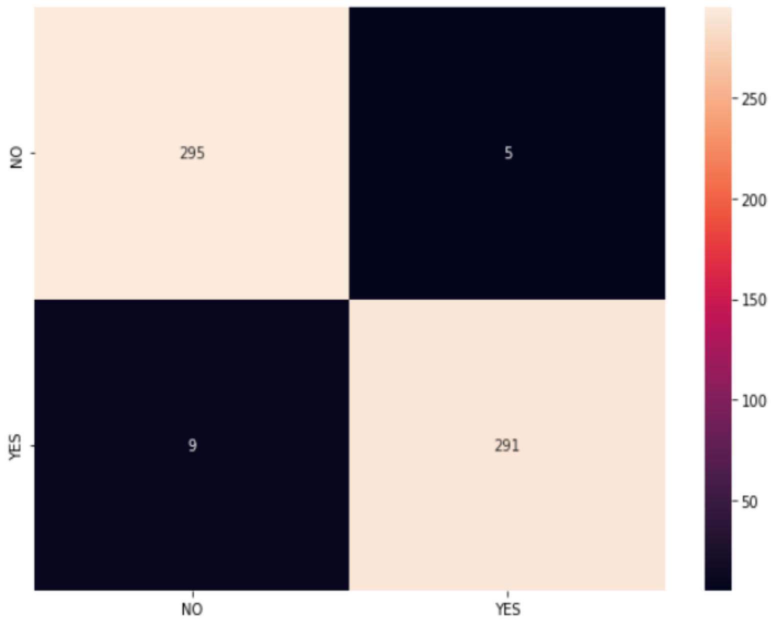

Figure 4.10: Confusion matrix of MobileNetV2.

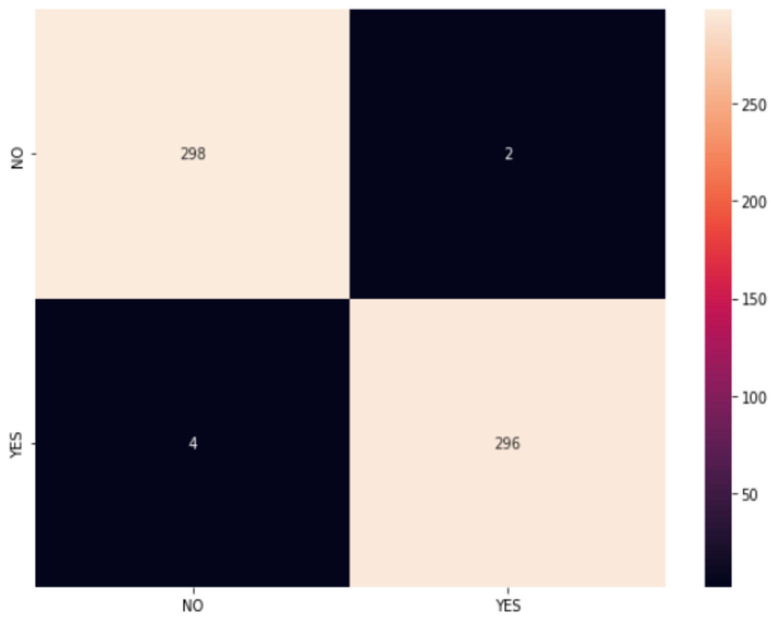

Figure 4.11: Confusion matrix of DenseNet201.

Figure 4.10 and Figure 4.11 are the demonstration of the confusion matrices of MobileNetV2 and DenseNet201 models respectively.

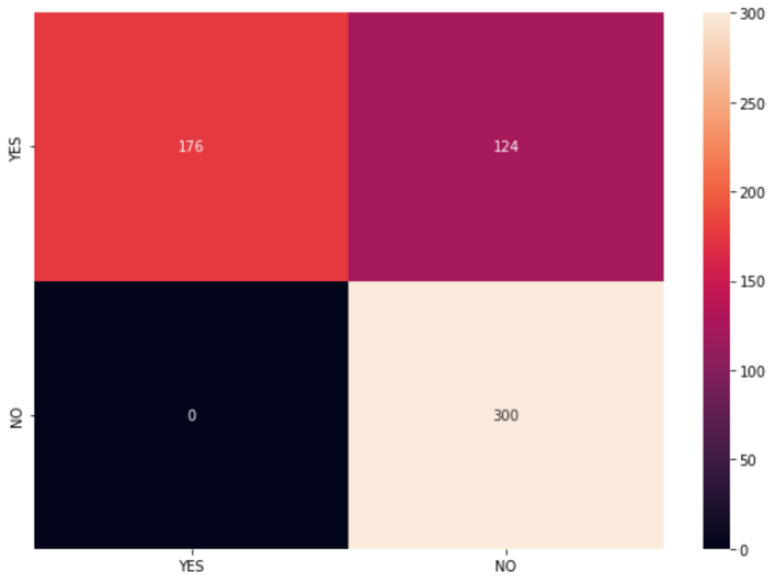

Figure 4.12: Confusion matrix of ResNet50.

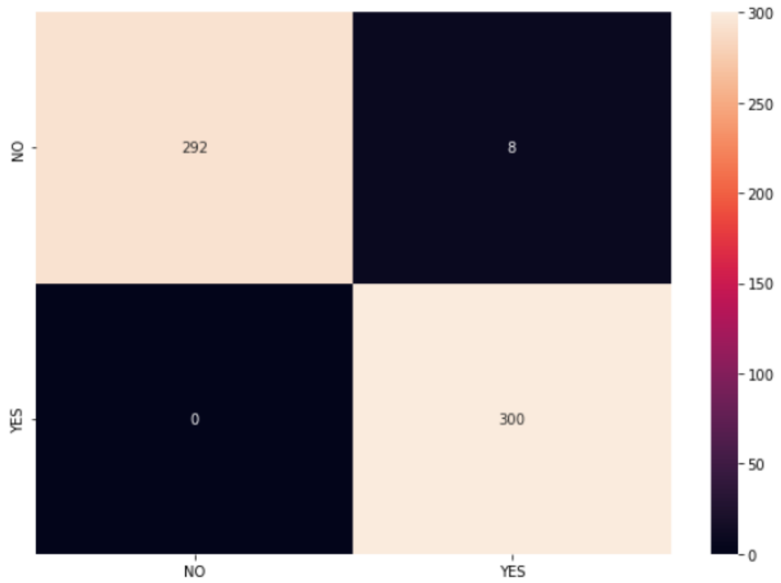

Figure 4.13: Confusion matrix of ResNet101.

Figure 4.12 and Figure 4.13 are the demonstration of the confusion matrices of ResNet50 and ResNet101 models respectively.

Figure 4.14 is the demonstration of the confusion matrix of VGG19 model.

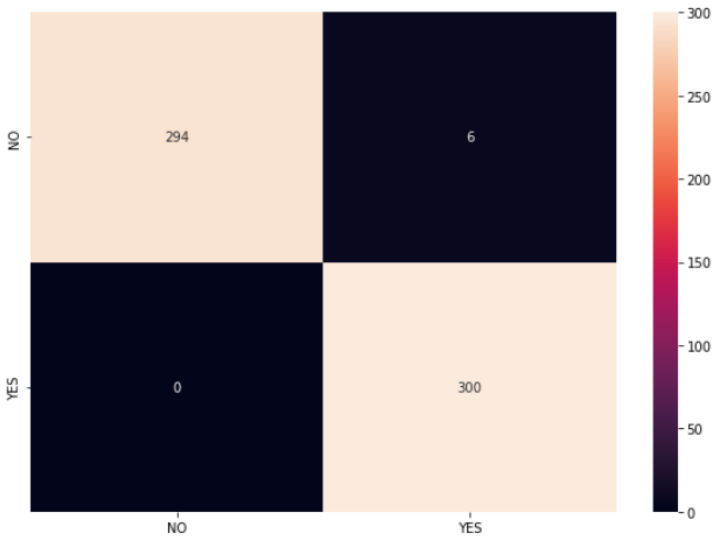

Figure 4.14: Confusion matrix of VGG19.

Table 4.2 compares the performance of the models based on accuracy, precision, recall, and f1-score.

Table 4.2: Comparison of the performance of the models.

	CNN	*Inception V3*	*MobileNetV2*	*DenseNet 201*	*ResNet50*	*VGG19*	*ResNet101*
Accuracy	98.17	96.8	97.6	99	79	98.95	98.6
Precision	99	97	98	99	85	99	99
Recall	99	97	98	99	79	99	99
f1-Score	99	97	98	99	79	99	99

4.3 Discussion

This section explains about the setup of experimental work of our study and the comparative analysis of our used algorithm when they are implemented on the Brain tumor MRI data. In this research, our aim was to identify the brain tumor image from the image data combination of healthy (no tumor) and unhealthy (tumor present) brain scans. The models were tested on the dataset and they provided accuracy as follows, CNN achieved an accuracy of 98.17% to accurately identify brain tumor, InceptionV3 got 96.8% accuracy in identification, MobileNetV2 had 97.6% accuracy, DenseNet201 had 99% of accuracy, ResNet50 had 79% accuracy, VGG19 got 98.95% accuracy and ResNet101 obtained 98.6% accuracy. It is rapidly apparent that, DenseNet201 model has achieved better result than other models in terms of identifying brain tumors with more precision. But the model ResNet50 has obtained only 79% of accuracy to correctly identify brain tumor which was relatively lower than all other model's accuracy. So, comparison of the models proves that DenseNet201 with 99% accuracy is the best performing model to accurately identify brain tumor. Through our research we want to suggest the medical sector to utilize the DenseNet201 model to detect brain tumor as it is the best performer according to our study.

CHAPTER 5

Impact on Society, Environment and Sustainability

5.1 Impact on Society

Most valuable possession anyone can have their own life. But occasionally certain illnesses do harm to people's lives, making life tough. It includes brain tumors. One of our bodies' most vital organs is the brain. Many patients receive a brain tumor diagnosis each year. Many lives are lost when improper care is not provided. In the United States, 83,570 persons had a brain tumor diagnosis, and 18,600 of them passed away. When viewed globally, the figure rises significantly. As a result of its annual death toll of thousands, brain tumors represent one of society's largest concerns. Most aberrant cells found in tumors. An internal growth of aberrant cells is called a brain tumor. Manual disease detection is done by the doctors. There is always a potential that a doctor will make a mistake because they are also people. In addition, occasionally a brain tumor's late identification can be the difference between life and death. The patient has a better probability of surviving the earlier the tumor can be found. Once more, there are many different kinds of brain tumors there. Therefore, if a brain tumor is detected manually, it can be highly challenging and time-consuming. As a result, the patient's chances of recovering are reduced. This problem will be resolved by our project. The major focus of our study is an automated brain tumor detection. which primarily uses MRI images to detect brain tumors. Our project's primary objective is to identify brain tumors more rapidly and accurately than is now possible. Deep learning techniques were used to complete the entire project. Compared to the other approaches of brain tumor identification, the DenseNet-201 model produced better results. This enables our effort to swiftly and precisely identify brain tumors. Our project's objective is to benefit society at large and medical care. Patients and their families frequently receive our assistance. Brain tumors may develop into cancer if they are not found early enough. It can put burden on the patient's family, as well as the sufferer, both financially and mentally. Since the expense of treating cancer is very high, brain cancer may result in financial loss. This can result in morbidity and early mortality. Sometimes, family may occasionally lose one of its only income producers. It might completely wreck the family's financial situation. Family members and the patient may experience worry, distress, and depression as a result of these. The cost of the therapy increases significantly if the brain tumor is not discovered early, and medication waste might have a detrimental environmental impact. Consequently, how a brain tumor may impact society as a whole. In these cases, our project is usually helpful. The procedure of detecting the brain tumor is sped up. resulting in the patient receiving therapy earlier. A brain tumor can usually be recovered from with earlier treatment. As a result, the patients and their family can live healthier and more regular lives like the rest of us. thus, the social impact of our initiative.

5.2 Impact on Environment

Brain tumors may be regarded as a curse on humanity. This sickness has claimed numerous lives over a long period of time. The brain is among the most vital organs in the human body. Essentially, a brain tumor is an aberrant cell proliferation. A significant brain tumor may result in brain cancer. Due to the lack of a treatment for brain cancer, many people pass away from it every year. Preventing it is therefore the answer. But occasionally, the task is quite challenging. If a brain tumor can be found in its early stages, the survival percentage in most situations is significantly higher. Magnetic resonance imaging is employed to do that. However, the same technique is still applied to diagnose a delicate illness like a brain tumor. The majority of the time, when doctors examine MRI images, brain tumors are found. However, doctors are also fallible human beings, and human beings make mistakes. Again, a technical problem could occur occasionally. An unclear MRI image can be perplexing. An error in judgment can result in significant loss. Worldwide, thousands of people receive a brain tumor diagnosis each year. In order to find brain tumors, thousands of MRI pictures are used. Plastic is mostly used to construct the images produced by MRI machines. because plastic does not decompose in soil. Because of the soil pollution it creates, it greatly harms the ecosystem. Additionally, burning the plastic is useless because it pollutes the air. As a result, the disposal of physical MRI images significantly damages the environment. It could be bad for both people and the entire eco system. Not to mention the toxic waste of the cancer-treating medications if a brain tumor is not found sooner. This problem will also be resolved by our project. In our project, deep learning methods were employed to create an automated brain tumor detector. Our project's major objective is to automatically detect brain cancers with greater accuracy and speed than the current method of doing so. There is less need for actual MRI images because our project is automated and uses deep learning techniques. This means that our project can only detect a brain tumor using digital data. It has the potential to significantly affect the environment. There will be less actual MRI images if brain tumors can be identified using our automated technology in the majority of the locations. As a result, the use of plastic will decrease because these MRI reports are made of plastic. Thus, the soil and air will be preserved. that might result in a better environment. Additionally, a healthy environment leads to a healthier way of life for those who inhabit it. We want to improve the survival rate of people with brain tumors while also having a positive influence on the environment. And our project does it in a practical way. the environmental effects of our project.

5.3 Ethical Aspects

Our study aims to assist medical professionals in more effectively and swiftly identifying brain tumors. Additionally, our project will be able to assist patients in receiving correct results. Negative test results can occasionally have disastrous effects. incorrect therapy can result in numerous consequences. It sometimes causes a number of ailments. That can lead to a number of serious financial issues. To complete our project, we have used datasets from a website with a publicly accessible data repository named "Kaggle". Additionally, we intend to gather real-life data from medical facilities like hospitals and clinics. These figures are going to be more precise. The precision of our study will rise when more precise datasets are used. Because of this, we can provide patients improved brain detection methods that will benefit them more. As a result, all of our work is morally acceptable.

5.4 Sustainability Plan

In our research, we have used deep learning methods to find tumors. By utilizing deep learning technologies our research can aid doctors in tumor detection, as well as in determining the extent of the tumor and the actual status of the patient. Our research will improve the process of detecting brain tumors from brain MRI pictures by utilizing several types of algorithms. The doctor will find brain tumor-affected patients at an early stage with ease. We will assemble more data from numerous databases in order to continue our research. We'll also go to the hospital and talk to the workers and patients there. Knowing that if we can speak with the hospitals authority to have their permission to share their data, then we will have a better chance of getting correct information. This can be a more reliable information source than the internet. Hospitals and other healthcare establishments will be where we collect the information. As a result, we will be able to detect brain tumors more precisely and quickly than previously, increasing their detection accuracy, of which countless lives can be saved.

CHAPTER 6

Conclusion, Recommendation and Future works

6.1 Summary of the Study

One of the most serious diseases today is a brain tumor. In recent years, brain tumors, which are frequently caused by brain cancer, have claimed a great number of lives. Only 36% of brain cancer patients survive for five years or more. The survival percentage of patients with brain cancer is extremely low because there is no specific treatment for it. However, patients' chances of survival can be improved by early diagnosis of brain tumors. Additionally, it occasionally takes longer to detect a brain tumor. It may result in really late treatment for brain detection. Additionally, a patient's likelihood of life may be reduced by delayed treatment for a brain tumor. Not to mention the financial hardship the patient's family may experience in the interim. We wished to assist in the automatic location and detection of brain tumors for this reason. This is able to improve the way patients are treated. In order to achieve our objectives, we first conducted research on how to create a model that can automatically detect brain tumors. After developing a model, we gathered a dataset on which to train the model. Then, in order to detect the brain tumors, we used deep convolutional networks. Prior to it, we used preprocessing and augmentation techniques. We have used seven algorithms to detect the brain tumor. Brain tumors have been detected using ResNet-101, Inception V3, ResNet50, DenseNet-201, VGG19, MobilenetV2 and CNN. We then compared the degrees of accuracy of the algorithms. This study has been done on how to create a model that can quickly identify brain tumors. We recommend to using the DenseNet-201 model. Which have provided incredibly high accuracy levels. We also computed the accuracy, precision, recall, and f1 score for each model for comparison. Where we have achieved a higher score using DenseNet-201 model.

6.2 Conclusion

Early brain tumor identification can improve a patient's chance of survival. Magnetic resonance imaging (MRI) has grown in popularity for detecting brain tumors. However, if the detection is carried out by a human, MRI detection may not always be accurate.
Consequently, brain tumors can be more accurately detected using MRI images. This study introduces several Deep Convolutional Neural Networks (CNNs), including

CNN, VGG19, ResNet-50, ResNet-101, InceptionV3, DenseNet-201, and MobileNetV2. Which has been evaluated using the MRI dataset for brain tumors. The first step in the procedure was preprocessing the images using the imageDataGenerator method of the Keras package using augmentation methods like rotation, height shift, width shift, horizontal flip, and shear. Additionally, they were cropped as part of the preprocessing. After that, brain tumors were detected using CNN, VGG19, ResNet50, ResNet101, InceptionV3, DenseNet201, and MobileNetV2. Then the accuracy level was compared. When we have compared to another model that we tested on our dataset, the accuracy of the DenseNet201 model is greater, providing 99% accuracy. And ResNet50 provided the lowest accuracy at 79%. For this reason, we recommend using the DenseNet201 model to detect brain tumors.

6.3 Implication for Further Study

In the near future, additional brain MRI scans will be gathered to add to the data. The accuracy can then be increased by combining these results with our dataset. In the future, our research will make use of real-time data from numerous hospitals and medicals.

References

[1] Raza, A., Ayub, H., Khan, J.A., Ahmad, I., S. Salama, A., Daradkeh, Y.I., Javeed, D., Ur Rehman, A. and Hamam, H., 2022. A hybrid deep learning-based approach for brain tumor classification. *Electronics*, *11*(7), p.1146.

[2] Sahu, M., Upadhyay, Y., Khoriya, N., Biswas, A., Chandrawanshi, M. and Patel, O., 2022, May. Deep Learning Techniques on Brain Images. In *Journal of Physics: Conference Series* (Vol. 2273, No. 1, p. 012026). IOP Publishing.

[3] Rajinikanth, V., Joseph Raj, A.N., Thanaraj, K.P. and Naik, G.R., 2020. A customized VGG19 network with concatenation of deep and handcrafted features for brain tumor detection. *Applied Sciences*, *10*(10), p.3429.

[4] Asif, S., Yi, W., Ain, Q.U., Hou, J., Yi, T. and Si, J., 2022. Improving Effectiveness of Different Deep Transfer Learning-Based Models for Detecting Brain Tumors From MR Images. *IEEE Access*, *10*, pp.34716-34730.

[5] Brain Tumor: Statistics, Cancer.Net Editorial Board, 02/2022 (Accessed on 29th November,2022)

[6] Ostrom, Q.T., Cioffi, G., Waite, K., Kruchko, C. and Barnholtz-Sloan, J.S., 2021. CBTRUS statistical report: primary brain and other central nervous system tumors diagnosed in the United States in 2014–2018. *Neuro-oncology*, *23*(Supplement_3), pp.iii1-iii105.

[7] Khan, H.A., Jue, W., Mushtaq, M. and Mushtaq, M.U., 2020. Brain tumor classification in MRI image using convolutional neural network. *Math. Biosci. Eng*, *17*(5), pp.6203-6216.

[8] Hossain, T., Shishir, F.S., Ashraf, M., Al Nasim, M.A. and Shah, F.M., 2019, May. Brain tumor detection using convolutional neural network. In *2019 1st international conference on advances in science, engineering and robotics technology (ICASERT)* (pp. 1-6). IEEE.

[9] Zhang, J.P.; Li, Z.W.; Yang, J. A parallel SVM training algorithm on large-scale classification problems. In Proceedings of the 2005 International Conference on Machine Learning and Cybernetics, Guangzhou, China, 18–21 August 2005; pp. 1637–1641.

[10] Sharma, A.K., Nandal, A., Dhaka, A., Koundal, D., Bogatinoska, D.C. and Alyami, H., 2022. Enhanced watershed segmentation algorithm-based modified ResNet50 model for brain tumor detection. *BioMed Research International*, *2022*.

[11] Lu, D., Polomac, N., Gacheva, I., Hattingen, E. and Triesch, J., 2021, June. Human-expert-level brain tumor detection using deep learning with data distillation and augmentation. In *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)* (pp. 3975-3979). IEEE.

[12] Noreen, N., Palaniappan, S., Qayyum, A., Ahmad, I., Imran, M. and Shoaib, M., 2020. A deep learning model based on concatenation approach for the diagnosis of brain tumor. *IEEE Access*, *8*, pp.55135-55144.

[13] Hu, A. and Razmjooy, N., 2021. Brain tumor diagnosis based on metaheuristics and deep learning. *International Journal of Imaging Systems and Technology*, *31*(2), pp.657-669.

[14] Choudhury, C.L., Mahanty, C., Kumar, R. and Mishra, B.K., 2020, March. Brain tumor detection and classification using convolutional neural network and deep neural network. In *2020 international conference on computer science, engineering and applications (ICCSEA)* (pp. 1-4). IEEE.

[15] Woźniak, M., Siłka, J. and Wieczorek, M., 2021. Deep neural network correlation learning mechanism for CT brain tumor detection. *Neural Computing and Applications*, pp.1-16.

[16] Çinar, A. and Yildirim, M., 2020. Detection of tumors on brain MRI images using the hybrid convolutional neural network architecture. *Medical hypotheses*, *139*, p.109684.

[17] Irmak, E., 2021. Multi-classification of brain tumor MRI images using deep convolutional neural network with fully optimized framework. *Iranian Journal of Science and Technology, Transactions of Electrical Engineering*, *45*(3), pp.1015-1036.

[18] Kang, J., Ullah, Z. and Gwak, J., 2021. Mri-based brain tumor classification using ensemble of deep features and machine learning classifiers. *Sensors*, *21*(6), p.2222.

[19] Almadhoun, H.R. and Abu-Naser, S.S., 2022. Detection of Brain Tumor Using Deep Learning. *International Journal of Academic Engineering Research (IJAER)*, *6*(3).

[20] Mahbub, M., Biswas, M., Miah, M., Mozid, A. and Kaiser, M.S., 2022. Deep Neural Networks for Brain Tumor Detection from MRI Images. In *Proceedings of the Third International Conference on Trends in Computational and Cognitive Engineering* (pp. 473-485). Springer, Singapore.

[21] Qureshi, S.A., Raza, S.E.A., Hussain, L., Malibari, A.A., Nour, M.K., Rehman, A.U., Al-Wesabi, F.N. and Hilal, A.M., 2022. Intelligent Ultra-Light Deep Learning Model for Multi-Class Brain Tumor Detection. *Applied Sciences*, *12*(8), p.3715.

[22] Ahmad, S. and Choudhury, P.K., 2022. On the Performance of Deep Transfer Learning Networks for Brain Tumor Detection using MR Images. *IEEE Access*.

[23] Musallam, A.S., Sherif, A.S. and Hussein, M.K., 2022. A New Convolutional Neural Network Architecture for Automatic Detection of Brain Tumors in Magnetic Resonance Imaging Images. *IEEE Access*, *10*, pp.2775-2782.

[24] Ketkar, N. and Moolayil, J., 2021. Convolutional neural networks. In Deep Learning with Python (pp. 197-242). Apress, Berkeley, CA.

[25] Weimer, D., Scholz-Reiter, B. and Shpitalni, M., 2016. Design of deep convolutional neural network architectures for automated feature extraction in industrial inspection. *CIRP annals*, *65*(1), pp.417-420.

[26] Hasan, M.Z., Ahamed, M.S., Rakshit, A. and Hasan, K.Z., 2019, July. Recognition of jute diseases by leaf image classification using convolutional neural network. In *2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT)* (pp. 1-5). IEEE.

[27] Teuwen, J. and Moriakov, N., 2020. Convolutional neural networks. In Handbook of medical image computing and computer assisted intervention (pp. 481-501). Academic Press.

[28] Agarap, A.F., 2018. Deep learning using rectified linear units (relu). *arXiv preprint arXiv:1803.08375*.

[29] Sun, M., Song, Z., Jiang, X., Pan, J. and Pang, Y., 2017. Learning pooling for convolutional neural network. Neurocomputing, 224, pp.96-104.

[30] Basha, S.S., Dubey, S.R., Pulabaigari, V. and Mukherjee, S., 2020. Impact of fully connected layers on performance of convolutional neural networks for image classification. *Neurocomputing*, *378*, pp.112-119.

[31] Hu, R., Tian, B., Yin, S. and Wei, S., 2018, November. Efficient hardware architecture of softmax layer in deep neural network. In *2018 IEEE 23rd International Conference on Digital Signal Processing (DSP)* (pp. 1-5). IEEE.

[32] Fettah, A., Goumidi, B. and Daho, M., 2022. Deep Learning Model for Magnetic Resonance Imaging Brain Tumor Recognition. *WAS Science Nature (WASSN) ISSN: 2766-7715*, *5*(1), pp.1-11.

[33] Sandler, M., Howard, A., Zhu, M., Zhmoginov, A. and Chen, L.C., 2018. Mobilenetv2: Inverted residuals and linear bottlenecks. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 4510-4520).

[34] Towards data science, available at <<https://towardsdatascience.com/review-mobilenetv2-light-weight-model-image-classification-8febb490e61c>> last accessed on 29-12-22 at 2:13 AM.

[35] Huang, G., Liu, Z., Van Der Maaten, L. and Weinberger, K.Q., 2017. Densely connected convolutional networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 4700-4708).

[36] Yu, X., Zeng, N., Liu, S. and Zhang, Y.D., 2019. Utilization of DenseNet201 for diagnosis of breast abnormality. *Machine Vision and Applications*, *30*(7), pp.1135-1144.

[37] ÇETİNER, H. and ÇETİNER, İ., 2022. Classification of Cataract Disease with a DenseNet201 Based Deep Learning Model. *Journal of the Institute of Science and Technology*, *12*(3), pp.1264-1276.

[38] He, K., Zhang, X., Ren, S. and Sun, J., 2016. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 770-778).

[39] Demir, A., Yilmaz, F. and Kose, O., 2019, October. Early detection of skin cancer using deep learning architectures: resnet-101 and inception-v3. In *2019 medical technologies congress (TIPTEKNO)* (pp. 1-4). IEEE.

[40] Simonyan, K. and Zisserman, A., 2014. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

[41] Mateen, M., Wen, J., Song, S. and Huang, Z., 2018. Fundus image classification using VGG-19 architecture with PCA and SVD. *Symmetry*, *11*(1), p.1.

[42] Jaworek-Korjakowska, J., Kleczek, P. and Gorgon, M., 2019. Melanoma thickness prediction based on convolutional neural network with VGG-19 model transfer learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops* (pp. 0-0).

[43] Simonyan, K. and Zisserman, A., 2014. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

PLAGIARISM REPORT

ZW

ORIGINALITY REPORT

25%	18%	16%	14%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	dspace.daffodilvarsity.edu.bd:8080 Internet Source	5%
2	Submitted to Daffodil International University Student Paper	3%
3	www.frontiersin.org Internet Source	1%
4	Divjot Kaur, Silky Goel, Rahul Nijhawan, Siddharth Gupta. "Analysis of Brain Tumor using Pre-trained CNN Models and Machine Learning Techniques", 2022 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), 2022 Publication	1%
5	www.researchgate.net Internet Source	1%
6	Haitham Alsaif, Ramzi Guesmi, Badr M. Alshammari, Tarek Hamrouni, Tawfik Guesmi, Ahmed Alzamil, Lamia Belguesmi. "A Novel Data Augmentation-Based Brain Tumor	<1%