MULTICALSS BRAIN TUMOR RECOGNITION USING CONVOLUTIONAL NEURAL NETWORK

By

Jahid Hasan Jony

ID: 201-15-13852

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

Supervised By

Mr. Dewan Mamun Raza

Lecturer (Senior Scale)

Department of Computer Science and Engineering

Faculty of Science and Information Technology

Co-Supervised By

Md. Ferdous Ahmed Foysal

Lecturer

Department of Computer Science and Engineering

Faculty of Science and Information Technology

DAFFODIL INTERNATIONAL UNIVERSITY
DHAKA, BANGLADESH

APPROVAL

This Project/internship titled **Multiclass Brain Tumor Recognition Using Convolutional Neural Network**, submitted by **Jahid Hasan Jony**, ID No: **201-15-13852** 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 **19th January 2023.**

BOARD OF EXAMINERS

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

Md. Sadekur Rahman — **Internal Examiner**
Assistant Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Fahad Faisal — **Internal Examiner**
Assistant Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Dr. Mohammad Shorif Uddin — **External Examiner**
Professor
Department of Computer Science and Engineering
Jahangirnagar University

DECLARATION

I hereby declare that this research has been done by under the supervision of **Mr. Dewan Mamun Raza, Lecturer (Senior Scale), Department of Computer Science and Engineering,** Faculty of Science and Information Technology, Daffodil International University. I also declare that neither this research nor any part of this research has been submitted elsewhere for the award of any degree.

Supervised By:

Dewan Mamun Raza
Lecturer (Senior Scale)
Department of Computer Science and Engineering
Daffodil International University

Co-Supervised By:

Md. Ferdous Ahmed Foysal
Lecturer
Department of Computer Science and Engineering
Daffodil International University

Submitted By

19.01.23

Jahid Hasan Jony
ID: 201-15-13852
Department of Computer Science and Engineering

ACKNOWLEDGEMENT

At First, I would like to express our heartiest thanks and gratefulness to almighty God for His divine blessing makes us possible to complete the final year thesis successfully.

I truly appreciate and want to express my sincere gratitude to **Mr. Dewan Mamun Raza**, Lecturer (Senior Scale), Department of CSE, Faculty of Science and Information Technology, Daffodil International University, Dhaka. His in-depth knowledge and genuine interest in the subject of deep learning-based research enabled me to finally finish my research on "**Multiclass Brain Tumor Recognition using Convolution Neural Network**". This research effort was made possible by his never-ending patience, academic direction, constant encouragement, frequent and vigorous supervision, constructive criticism, invaluable advice, reviewing numerous subpar versions and revising them at all stages. I would like to convey my sincere appreciation to Professor **Dr. Touhid Bhuiyan**, Professor and Head, Department of Computer Science and Engineering, Faculty of Science and Information Technology, DIU, for his invaluable assistance and counsel in helping me complete my research study and also extends its sincere gratitude to the other faculty members and employees of Daffodil International University's department of CSE.

Finally, I would want to express my gratitude to all of the well-wishers, friends, family, and elders for their support and inspiration. Hard labor, as well as all of those inspirations and help, went into this study.

Last but not least, I must respectfully thank our parents for their unwavering love and patience.

ABSTRACT

Day by day the use of computers is increasing everywhere. Computer science is already widely used in the medical field. Brain tumor diagnosis can be performed using computer vision. This research applied several algorithms on this. Among them is the Convolution Neural Network (CNN), which is the most common application of CNN for image recognition challenges. This has been used with MRI images. The outcomes are fairly decent. Also applied VGC-16, MobileNetV2, and InceptionV3 on brain tumor MRI images. The experiment is conducted on a dataset of 3264 images containing four different types of brain tumor (glioma, meningioma, pituitary, and no tumor). It is tough to collect data from hospitals so primarily we collected data from online resources. For experiment first I preprocessed the image and then apply those algorithms. Among them, CNN gives us the best accuracy which is 95%. This study states the various algorithms performed on the same datasets and the best model.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1
INTRODUCTION

1.1 Introduction

The most significant organs in the human body are the brain. The normal lives of people are affected if there is a brain disease. Brain Tumor is one of them. Tumors can be detected in many parts of the human body. Among them, the most critical is to catch a tumor in the brain. In the brain, there are typically two different tumor forms. Primary tumors and secondary brain tumors. Tumors can come to the brain from different areas of the body. The majority of brain tumors are secondary. Primary brain tumors also have two parts, vinyl and malignant. It can range from brain tumors to cancer. There is no known cause for brain tumors so far! It is said that in 0.1% of cases, the common headache is from the tumor. Therefore, prevention and early detection of the tumor are essential. In the early stage, brain tumor segmentation has been done the use of a framework-based outline detection method. They used T2 image intensities to automatically separate brain tumors based on whether edema was present in the aberrant regions along with the tumor or not. [1]. In 2004 also showed that brain tumor segmentation using integrated can be done Bayesian Model Classification in order to bridge the gap between bottom-up affinity-based segmentation techniques and top-down generative model-based approaches, they introduce a new technique for the segmentation automatically of heterogeneous picture data. The paper's primary contribution is a Bayesian framework for soft model assignments that may be included in affinities calculations, which are typically model-free. They applied the method to the challenge of identifying and dividing brain tumors and edema in multichannel magnetic resonance (MR) volumes by integrating the obtained model-aware affinities into the multilevel segmentation by weighted aggregation algorithm [2]. 3D CNN can also be exploited for brain tumor segmentation. They suggested an effective 3D residual neural network (ERV-Net) with lower computational complexity and GPU memory consumption for segmenting brain tumors. In ERV-Net, a computation-efficient network called 3DShuffleNetV2 is initially used as an encoder to free up GPU memory and increase ERV-efficiency. Net's Then, to prevent degradation, the Res-decoder, a decoder containing residual blocks, is implemented. Furthermore, to address the issues of data imbalance and network convergence, a fusion loss function made up of dice loss and cross-entropy loss is devised. The outcomes showed that ERV

Net was the most effective and the least amount of computational complexity [3]. In 2015 was shown that image segmentation can be done with hybrid clustering as the two techniques are integrated simultaneously. They showed that The K Min algorithm can certainly detect brain tumors faster than Fuji Si Mins. To provide precise brain tumor detection, they added thresholding and level set segmentation phases afterward. The benefits of K-means clustering for image segmentation in terms of minimal computing time can be obtained by using the proposed technique. Additionally, it can gain from the Fuzzy C-means' advantages in terms of precision. By contrasting the accuracy, processing speed, and performance of the proposed method for image segmentation with those of a few state-of-the-art segmentation algorithms, its performance was assessed. By comparing the outcomes with the original, raw variations of each processed image, the accuracy was evaluated [4]. If apply U-Net architecture to glioma segmentation there are still some problems. For instance, in MRI, irritating discrete spots always manifest themselves as high intensity patterns. While learning features specific to tumor regions with tiny proportions is challenging due to the unequal distribution of classes between areas with gliomas and those with normal tissue, the fuzziness of glioma region boundaries may make it challenging for DNN to distinguish each tissue class effectively. To address this, they suggested TIU-Nets to improve accuracy by enhancing border information [5]. For localized tumor regions, the YOLOv2-inceptionv3 model can be more accurately used. Lesion enhancement, feature extraction, and selection for classification, localization, and segmentation are the four phases of their suggested method. Images obtained by magnetic resonance imaging (MRI) are noisy because to picture acquisition issues and magnetic Feld coil fluctuations, among other things. To reduce noise, they applied a homomorphic wavelet filter. They then retrieved features from the Inceptionv3 pre-trained model and used a genetic algorithm with non-dominance to choose informative features (NSGA). Tumor slices are passed to the YOLOv2-inceptionv3 model, which was created to determine where the tumor is located, after the optimized features have been forwarded for classification. In this model, features are extracted. from the depth-concatenation (mixed-4) layer of the inceptionv3 model and supplied to the YOLOv2 [6].

1.2 Objective

Here, we compared many algorithms on a single dataset to determine which was the most effective. Four types of brain tumors can be properly classified by the technique. With the use of image processing methods, acquired images are preprocessed. Four classifiers have been utilized for classification, including CNN, VGG-16, MobileNetV2, and InceptionV3. This paper's major contribution is as follows:

- My objective is to learn how to categorize and identify various types of brain tumors.
- to create a model that can identify any type of brain tumor.
- Using classifier algorithms, it is possible to visualize some analytical analyses of different types of brain tumors, such as gliomas, meningiomas, pituitary tumors, and no tumors.
- CNN is a better classifier for recognizing brain tumors compared to others.
- The machine learning-based computer vision work can recognize four types of brain tumors.
- This suggested algorithm was also trained on non-tumor MRI images, indicating that this work can recognize normal brain tissue or no brain tumor.
- In comparison to the other models, one (CNN) attained a satisfactory level of recognition accuracy.

1.3 Motivation

I am very much interested to do something using ML and Image Processing. My interested field is Image Processing. So, I decided to do something where image processing would apply. Then, start searching in google scholar using some image processing keywords. Find some disease classification using image processing, I decide to do brain tumor classification using some image processing algorithms. Then I read some paper using image processing techniques, most of them are did image segmentation but normally image classification with different algorithms is few. So, I decide that I'll do something using image classification and apply different algorithms and compare each algorithm and will suggest which is best. Finally, I reached my topics it called **"Multiclass Brain Tumor Classification Using Convolution Neural Network"**. These piqued my curiosity in do some research on this topic. My work is completely based on image processing under Machine Learning algorithms.

1.4 Rational of the study

Of course, there is plenty of work done on Image Processing and Machine Learning. But there are a few works done on classifying brain tumors with multiclass having no_tumor data. Therefore, my work offers a fresh perspective while applying several algorithms to it. I make every attempt to create my own model in order to create a more effective application in the field.

Nowadays Machine Learning uses everywhere, people are trusting ML gradually. My work is using image processing based on Machine Learning algorithms. Image Processing method has already been applied in medical sectors, this made the medical field efficient and modern. My work can help to detect brain tumors using MRI images as input.

1.5 Research Questions

I found it quite difficult to finish this research. The researchers would like to suggest the following questions to communicate these sentiments and consequences in order to have a realistic, effective, and correct answer to the situation.

- Different types of brain tumors are used in this work?
- What kind of effects can be in the real life after affected Brain Tumors in humans?
- How MRI images are implemented in this work?

1.6 Expected Outcomes

There are certain statements in this section if they were our primary anticipated outcome. In light of the developed model and training dataset, the objective of this research is to develop an algorithm or complete, efficient procedure that can recognize brain cancers.

- CNN based Brain Tumor Classification.
- Doctors can rely more on machine.
- Tumors can be detected more accurately.

1.7 Layout of the report

In chapter 1, the project's aim, motivation, research questions, and expected results are explained together with an overview of the project's overall structure.

In chapter 2, discusses work that has already been done in this subject. The scope that resulted from their field's constraint is then demonstrated in this second chapter's subsequent portion. Finally, the main hurdles or impediments to this research are described.

In chapter 3, the theoretical discussion around this research endeavor is discussed. In order to address the theoretical component of the research, this chapter elaborates on the statistical methods utilized in the study. This chapter also exhibits the use of procedural procedures by CNN and a machine learning classifier.

In chapter 4, the experimental findings, performance assessment, and result discussion are presented This chapter includes a few experimental images to help the project be realized.

In chapter 5, covered the study's summary, next steps, and conclusion. This chapter is in charge of demonstrating how the entire project report complies with recommendations. The chapter is concluded by demonstrating the limits of our efforts, which may affect other people's future employment opportunities in this industry.

CHAPTER 2

Background Study

2.1 Introduction

This section will go through relevant works, a summary of the research, and issues with this study. We will discuss other research publications' findings, techniques, and accuracy as they apply to our work in the section on comparable studies. Under the heading of research summaries, we shall list our related work. We'll discuss how we improved accuracy in the section on difficulties.

2.2 Related Works

Brain tumors can be treated in a variety of ways. Brain Tumor segmentation and object detection are possible. Many researchers have accomplished two goals at the same time. However, machine vision-based brain tumor segmentation and object detection have received relatively little attention. M. Prastawa et al. (2004) performed a framework based on outlier detection. In their paper they worked on three real datasets. They have divided the segmentation framework into three parts. They used a novel method to automatically segregate the tumor and surrounding edema in non-enhancing multichannel MRI [7]. S. Krishnakumar and K. Manivannan (2020) Have done segmentation and classification in the same manner. They used the K means algorithm for this. The data was initially pre-processed. And it appears to be required [8]. Francisco Javier Díaz-Pernas et al. in 2021 presented that automatic brain tumor detection and segmentation using the Deep Convulsion Neural Network. If compare it with other works, they use the input image with three spatial scales in different processing ways. Their classification has achieved maximal accuracy, according to the dataset. This is higher than other techniques at 0.983 [9]. Hassan Habib et al. (2021) applied hybrid approach for brain tumor segmentation. For brain tumor segmentation, classification, and feature extraction, they utilized a hybrid method. Image acquisition, image preprocessing, image segmentation, and feature extraction are all part of their proposed technique. For applying hybrid method even, they achieved more than 90% accuracy [10]. Enhanced Encoder-Decoder networks can also be used to segment images of brain tumors. Mobeen Ur Rehman and et al. (2021) they have proposed, Encoder-Decoder network for brain tumor segmentation. For that they use three different data sets, BraTS2017, BraTS2018 and BraTS2019. When compared to other network architectures, their suggested BrainSeg-Net comes out on top

[11]. Machine learning, Deep Learning are used for brain tumor detection or segmentation of MRI images. He Huang (2021) used machine learning to divide the segmentation process into two categories: supervised and unsupervised. KNN, Bayes, and ANN are examples of supervised learning algorithms; unsupervised learning includes clustering techniques like K-Means, FCM, etc. To segment brain tumors, they employ a deep multi-task learning architecture [12]. Brain tumor segmentation utilizing u-net architecture has been the subject of extensive research. But, Sourodip Ghosh et al. (2021) they applied U-Net Architecture with VGG-16 for segmenting brain tumors. And in comparison, to basic U-net Architecture and improved U-Net architecture VGG-16, the updated VGG-16 gave them a little boost in accuracy [13]. For multi-class segmentation problem Guotai Wang and et al. (2018) applied Cascade Anisotropic Convolution Neural Network. They experimented it on BraTS 2017 dataset. It is used on three different hierarchical levels: the entire tumor, the tumor core, and the strengthen tumor core [14]. Kaggle arrange dataset competition, for BraTS 2018 dataset, Andriy Myronenko (2019) won first place. He applied Autoencoder Regularization for 3D MRI Brain Tumor Segmentation. It's also based on encoder-decoder architecture [15]. By adding more modules to the U Net Architecture, brain tumors can also be detected. Geena Kim (2018) used Deep Fully CNN for Brain Tumor Segmentation. She tried with four model, Mini U-Net, Mini U-Net with Double Convolutional Layers, Mini U-Net with Inception Modules and Mini U-Net with Dense Module [16]. LinkNet network also used for segmentation. Zahra Sobhaninia and et. al applied a new method for CNN to automatically segmentation brain tumors. They used Deep Learning by Type Specification Sorting of Images. For doctors their method can be made a simple and useful tool [17]. There are many popular algorithms for segmentation an image. SVM is one of them. It can be use along with CNN. In 2020, Wentao Wu and et al. used the Intelligent Diagnosis Method. They segmented MRI brain tumors using Deep Convolutional Neural Network and SVM algorithms. When the parameter is huge and there are large losses of information in the encoding-decoding process, the deep convolutional network has a difficulty [18]. Sometimes data need to be pre-processed as well as post-processed. M. Usman Akram and Anam Usman done three stages in their research work, first they preprocessed their MRI mage data, secondly, they done global threshold segmentation and thirdly they have done post-processing. For Brain Tumor Detection and Segmentation, they applied Computer Aided System [19]. Hao Dong and et al. (2017) showed U-Net based fully Convolutional Networks can be used to recognize and segment brain tumors [20]. The

identification, segmentation and the detection of tumor can be done by at one research work. N. Varuna Shree and T. N. R. Kumar (2017) have performed DWT and probabilistic neural networks were used to identify and classify brain tumors, as well as feature extraction from MRI images [21]. Considering the research works described above, this can conclude that there have been many works done for brain tumor detection but every work has a different way. They are not sufficient and proper enough to? Still a lot of studies can be contributed in this research area. also list out a few limitations after analyzing the above research works.

2.3 Research Summery

Convolutional Neural Network (CNN) is a subset of a machine learning. This is specially used for Image recognition and with image datasets. CNNs are the ideal network architecture for detecting and recognizing objects in deep learning, even if there are other types of neural networks available. Because of this, they make outstanding candidates for positions in computer vision and situations where precise object recognition is necessary, including in self-driving cars, facial recognition, or illness categorization.

As we know CNN is used for complex data such as image data, in my thesis work I used MRI images as an input data. For that I used CNN for classifying the images.

1x1	**1x0**	**1x1**	**0**	**0**
0x0	**1x1**	**1x0**	**1**	**0**
0x1	**0x0**	**1x1**	**1**	**1**
0	**0**	**1**	**1**	**0**
0	**1**	**1**	**0**	**0**

Input Image X Filter

4		

Convolved Features

Figure: 2.3.1 Convolution of a filter over 2D Images

The yield matrix can be measured and estimated using a condition. Prepared to see a condition. Where,

n_{out} - Output dimension

n_{in} - Input dimension

f - Window size

s- Stride

$$n_{out} = floor\left(\frac{n_{in} - f}{s}\right) + 1 \quad \text{.. (i)}$$

The given equation is used to determine the dimension's output.

Frequently, the convolution layer and the pooling layer are adjacent. It was mostly utilized for memory reduction and quick calculations. The volume is lowered. Max pooling is one of the most well-liked layers in CNN. The maximum number is determined from the network once a component has been configured.

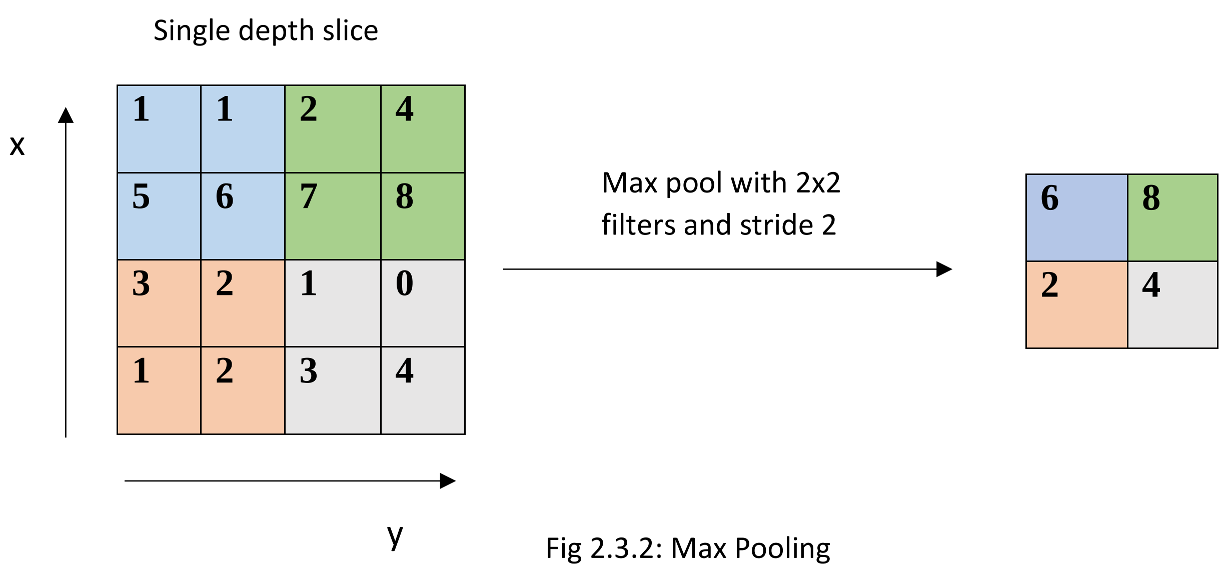


Fig 2.3.2: Max Pooling

The fully connected layer takes a 2D or 3D cluster from the previous layer and transforms it into a 1D array. A convolutional neural network's yield layer displays the probability of the classes.

The "Softmax" function is used to compute it. The prerequisites for estimating probability are described below.

$$\boldsymbol{\sigma(x_j) = \frac{e^{x_j}}{\sum_i e^{x_i}}} \quad \text{.. (ii)}$$

2.4 Challenges

There were several difficulties I encountered while working on my thesis. such as choosing a topic. There are many worthwhile research topics, and much previous work has been done. I choose to focus on the medical and health industry utilizing machine learning as my area of interest. After that, I ran into trouble gathering medical data. Although I obtain the data from online sources, working with medical data is difficult since it is so sensitive. Because of my PC's poor configuration, I had different challenges during the training and strove to be as patient as possible. I'm glad I was able to conquer every challenge.

CHAPTER 3

RESEARCH METHEDOLOGY

3.1 Introduction

I will go into more detail about the workflow of our cutting-edge method in this section to identify the sort of brain tumor it is. The gathering of data, processing of the data, and the proposed model are some of the main topics that are also explained with the appropriate equations, graphs, tables, and descriptions. The Brain Tumor Classification (MRI) dataset and recommended CNN-based model were both employed in this study. The chapter is concluded by providing clarification of the factual assumptions supporting our thesis as well as a thorough understanding of the conditions for implementation.

3.2 Workflow

The workflow for this study consists of a number of processes, including model selection, data processing, data resizing, and data collection.

Stage 1 – Data Collection: I searched everywhere for sources of the datasets I need. I then gathered data from online sources. Data collection was quite difficult.

Stage 2 – Data Processing: After being collected from different sources, the data have been analyzed class by class. There are a lot of noisy and inaccurate data. I manually process such data initially before moving on to the implementation of the selected dataset.

Stage 3 – Data Resize: Data have been resized after processing on a class-by-class basis. We had to go through image resizing as training. I refrained from using the augmentation strategy as there was satisfying image data.

Stage 4 – Model Selection: To improve accuracy, we choose our model, train it, and assess it against our data. Many people utilize convolutional neural networks. To increase the accuracy of our machine setup, we implemented many models; nevertheless, only one model was finally picked for the training and testing stage.

Stage 5 – Performance Evaluation: In this part, all of the results are presented as graphs. These procedures provided us with a few accuracy graphs showing accuracy and validity loss after training and testing.

Stage 6 – Conclusion and Future Work: This section will provide a summary as well as a roadmap for more development.

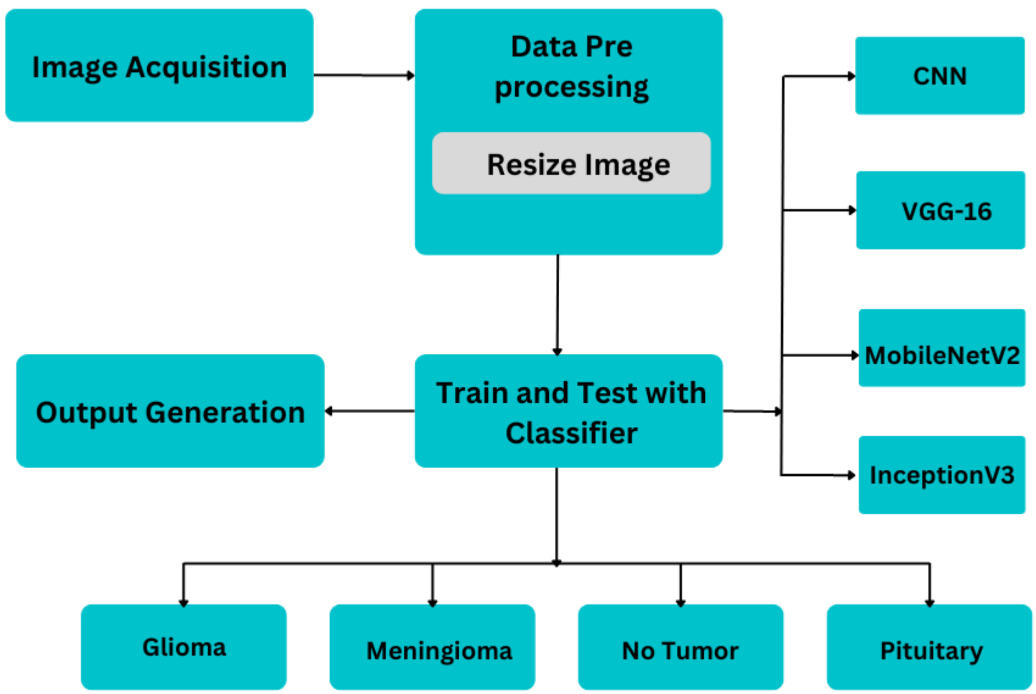


Fig 3.3: Working flow to classify the Multiclass Brain Tumors.

3.3 Image Acquisition

Image acquisition is the first stage in any computer vision-based research work. This is the procedure for collecting images from various sources. Of course, there needs to be a lot of images in order for the task to be satisfactory. So that this can succeed in achieving this intended result. You can either search for the images on your own or collect them from various sources. In this work gathered four different types of image data of brain tumors for this research. which include images of Glioma tumor, Meningioma tumor, Pituitary tumor, and No tumor. In Fig 2. shown the various tumor types.

3.4 Data Preprocessing

For better understanding to the machine image have to be well preprocessed. In image processing part can be done with image resizing, contrast enhancement, augmentation, color conversion if needed. In this work apply only image resize. In computer vision work image resizing is very important step for better accuracy.

3.5 Dataset Collection and Description

The datasets collected from Brain Tumor Classification (MRI) [22]. The datasets with four kind of brain tumors image: glioma tumors (926 images), meningioma tumors (937 images), pituitary tumors (901 images) and also datasets have no tumors MRI image (500 images). Each file contains a formation that includes different picture fields. These fields are labeled by (0 for indicates glioma tumor, 1 indicates for meningioma tumor, 2 indicates for no tumor and 3 indicates for pituitary tumor). This paper working on classify four different types of brain tumors, which is Glioma Tumor, Meningioma Tumor, Pituitary Tumor and No Tumor.

3.5.1 Glioma Tumor

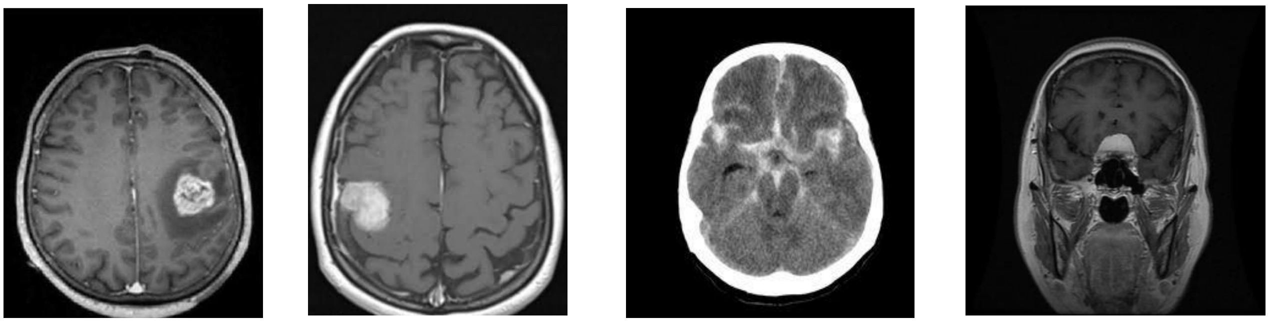
One such tumor that develops when glial cells proliferate unchecked is the glioma. Although some glioma tumors grow extremely slowly, some are cancerous.

3.5.2 Meningioma Tumor

The most prevalent tumors are meningiomas. This tumor has very low levels of very high risk. There are three phases to these tumors, with grade I being the most prevalent and least harmful. It also develops quite slowly. Grade II, which is comparatively less dangerous, is next. Meningioma of mid-grade is the term used for this. Grade III, which is dangerous, is the last. It expands rapidly. This grade also carries the risk of cancer.

3.5.3 Pituitary Tumor

Tumors are actually aberrant cell development. Anywhere can experience a tumor. A pituitary tumor is, in essence, a tumor that develops in the pituitary gland. most tumors in the pituitary are not cancerous.



A B C D

Fig 3.4: Tumors: A. Glioma; B. Meningioma; C. No Tumor; D. Pituitary

3.6 Brain Tumor Classification using CNN

For classifying images, convolution neural networks are a widely common approach. Even some researcher applied CNN for different datasets for experiment.[23]. In this paper tried different algorithms in a same dataset. And finally, came up with this final decision with CNN and suggest it for Multiclass Brain Tumor recognition. The general architecture of CNN plotted in Fig 3.

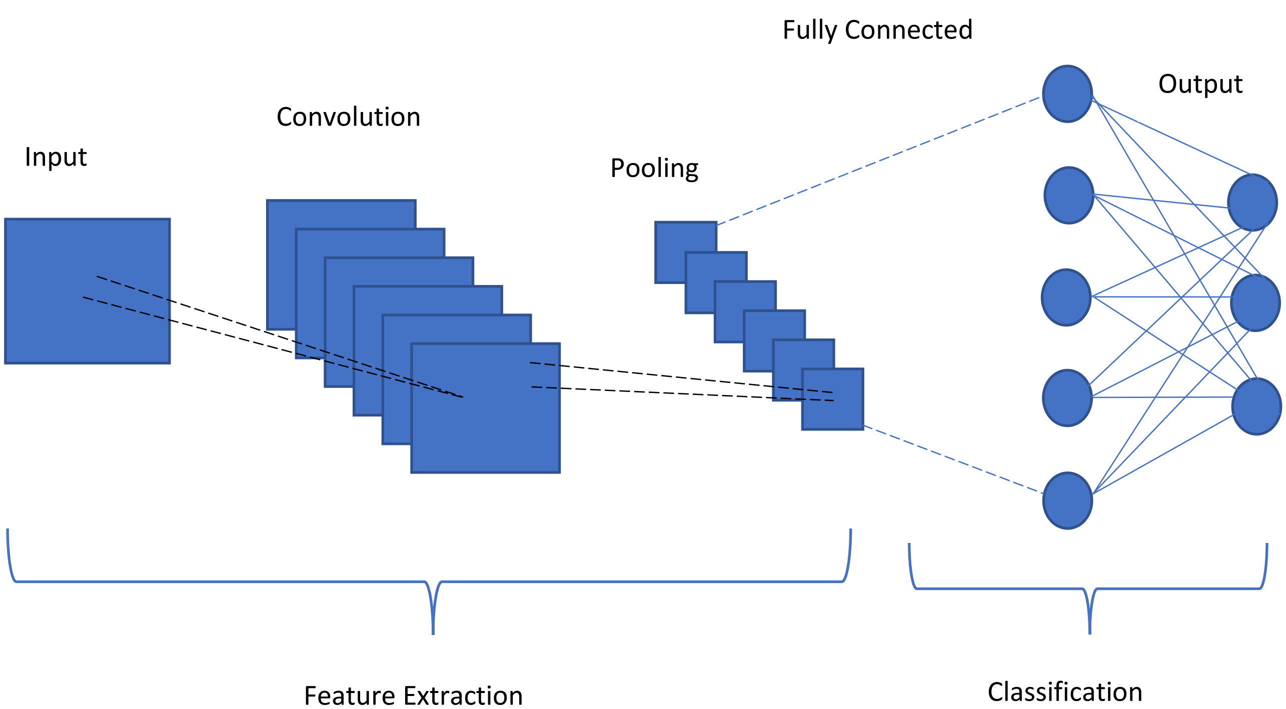


Fig 3.5: A general architecture of CNN

In this experiment applied image processing on several Brain Tumor MRI images in this study [16]. This used a straightforward Conv2D and Maxpool2D neural network to train them. Conv2D was employed by using 2D images. Everyone is aware that Maxpool2D is utilized in neural networks. Datasets were divided into two independent training and testing portions. There are 4 separate multiclass in each segment. The training data are used to train the model, while the test data are used for the model's final evaluation.

An overview of this suggested methods is shown in fig 3.4. The suggested Classification approach eliminates the necessity for independent feature extraction. Many researchers doing feature extraction in their implementation part [24]. In this research work scale each image to 30*30 pixels for data preparation. Due to the fact that diverse image shapes are not ideal for the model. The data for the images was then label.

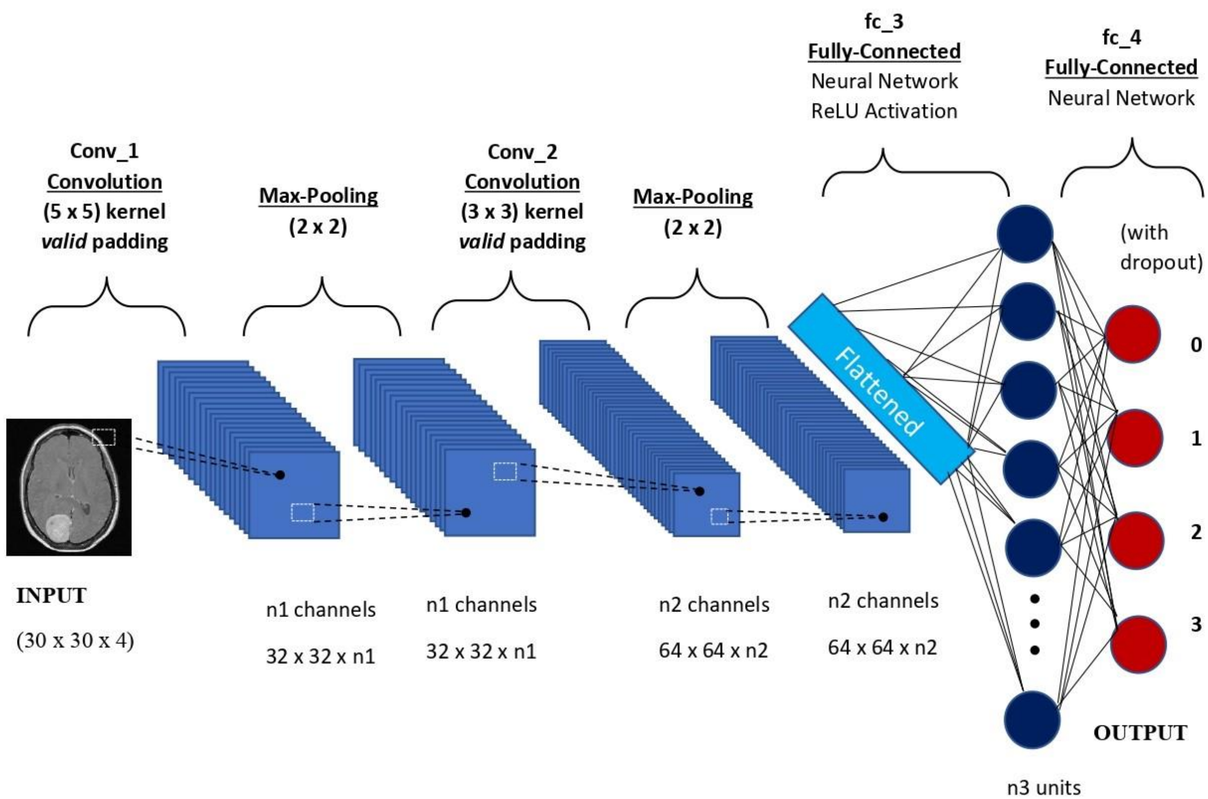


Fig 3.6: Suggested CNN Architecture

3.7. Train and Test of the Classifiers

The complete collection of data was divided into two groups: a train set that had 80% of the images and a test set that contained 20% of the images. Here, this research used 80% of the training data and 20% of the testing datasets to train each classifier. For each classifier, a 5x5 confusion matrix is constructed. To identify the multiple categories of brain tumors, this research work used four classifiers. Summarizes the specifications of the four operational classifiers are in Table 1.

Table 3.1. Summary of the four classifiers

Classifiers Name	Summery
CNN	Model: Sequential
	Epochs Used: 30
	Drop Out Value: 0.2
	Activation: SoftMax
VGG-16	Model: Sequential
	Epochs Used: 50
	Activation: SoftMax
MobileNetV2	Model: Sequential
	Epochs Used: 50
	Activation: SoftMax
InceptionV3	Model: Sequential
	Epochs Used: 50
	Activation: SoftMax

3.8 Implementation Requirements

After a careful examination of all pertinent statistical or theoretical concepts and methods, a list of prerequisites for such an image classification assignment has been developed. The likely prerequisites are,

Hardware/Software Requirements

- Operating System (Windows 7 or above)
- Hard Disk (Minimum 500 GB)
- RAM (Minimum 4 GB)

Development Tools

- Good internet connection
- Colab/Jupyter Notebook Environment
- Python

CHAPTER 4

EXPERIMENTAL RESULT AND DISCUSSION

4.1 Introduction

This section contains a description of the model's architecture for detecting brain tumors. The whole preparation for the demonstration was divided into a few parts, including the collecting of the datasets, the processing of the data, resizing of the data, the suggested model's depiction, and finally the planning of the model.

4.2 Analysis

The suggested model correctly classifies and predicts the medical images. The image-predicted tumor name is shown in the output. The output result is shown in Fig 4.2. Dataset have total 3264 images. 2870 images for training and 394 images for testing. For evaluating the performance of this classifier, this work has taken 394 (test image) MRI images of different brain tumors. Then obtained the images in a variety of sizes and perspectives for use in this experiment. We applied four classifier all of them accuracy is shown in Fig 4.1. The accuracy of the applied models is at a glimpse in Table 2. Table shown valid accuracy and also training accuracy.

4.2.1 InceptionV3

This is a model for image recognition. The study on image detection frequently uses this model. This Convolutional Neural Network is built on a learning model. Compared to V1, it has seen significant improvement. The accuracy of InceptionV3 is better than that of the previous version.

Fig 4.1: Accuracy and Loss set of InceptionV3

4.2.2 MobileNetV2

This is another Convolutional Neural Network model. There are 53 deep layers. The categorization of images such as keyboards, animals, pens, mouse etc. is done using this approach. It has acquired extensive feature representations as result.

Fig 4.2: Accuracy and Loss set of Inception MobileNetV2

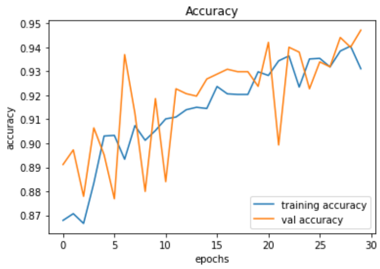
4.2.3 VGG-16

VGG-16 is also used to identify and categorize objects. 1000 images in 1000 categories can be classified by it. Because of its ease of usage with transfer learning, this method is the most well-known.

Fig 4.3: Accuracy and Loss set of Inception VGG-16

4.2.4 CNN

A powerful image-processing method is the convolutional neural network (CNN). Nowadays days, this method is used the most frequently to categorize images. Researchers frequently employ this method. It consists of three layers: a fully connected layer, a pooling layer, and a convolutional layer. This method is ideal for image identification.



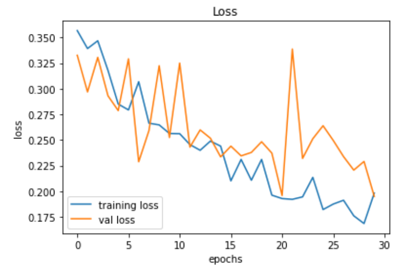
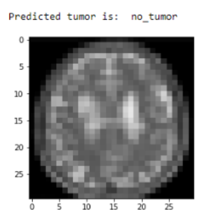
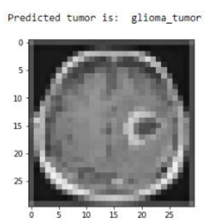
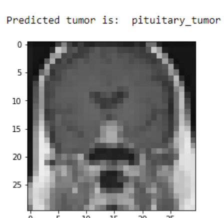


Fig 4.4: Accuracy and Loss set of Inception CNN

This graph Fig 4.2. demonstrates how accuracy increased while the loss function decreased for each epoch. MobileNetV2, VGG-16, and CNN trained using 50 epochs each for InceptionV3, and MobileNetV2 trained with 30 epochs for CNN. In Fig 6. Shows how accurately recognize the Brain Tumor from the input MRI images.

	Predicted Result is, No Tumor
	Predicted Tumor is, Glioma Tumor
	Predicted Tumor is, Pituitary Tumor

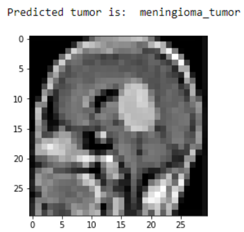
	Predicted Tumor is, Meningioma Tumor

Fig 4.5: Output of tumor images result of suggested CNN model

This is the model's outcome scenario. When given a 'no tumor' MRI image as an input model says ‘predicted tumor is no_tumor’ when given a pituitary MRI image as an input model says ‘predicted tumor is: pituitary_tumor’ and as follows other cases.

Table 4.1 Valid and Training Accuracy of applied Algorithms

Model	**Valid Accuracy**	**Training Accuracy**
CNN	95%	93%
VGG-16	80%	99%
MobileNetV2	76%	98%
InceptionV3	74%	96%

Table 4.1 demonstrated that CNN and InceptionV3 had the highest model accuracy of 95% and the lowest accuracy of 74%. VGG-16 and MobileNetV2 are respectively 99% and 98% accurate in training. The same dataset is used to apply each algorithm. The accuracy and the loss functions are plotted in Fig 4.1

CHAPTER 5

CONCLUSION, RECOMMENDATION AND FUTURE WORKS

5.1 Introduction

There are undoubtedly many research work on recognizing brain tumors. It has grown in significance in a number of applications. There are many different types of technology applied in the medical field nowadays, thus this strategy will develop a new technology with the primary objective of learning more about medicine and health.

5.2 Future Scope

As is aware, obtaining medical image data is difficult. More data can lead to more precise results. Even yet, this approach has excellent accurate results. On the same dataset, I have used four classifiers for my research project. There are various classifiers that may be used. To achieve more accuracy, my future goal is to build a stronger neural network.

- Use more Images data as train.
- Making deeper layer classifier will help.
- More data collection will provide more accuracy.

5.3 Conclusion

We are turning into the world we have dreamed of in this era of widespread digitization. In that world, the field of medicine and health greatly benefits from computer vision and machine learning. This study uses MRI images as the input for machine learning algorithms to identify the human brain tumor. This research presents a method for classifying various brain tumor types. 3264 images in total, containing 394 for testing and 2870 for training, were used to complete this work. Image resizing is used at the preprocessing stage. Since obtaining medical imaging is difficult and associated with privacy concerns, obtaining a significant amount of data is difficult. Even then, this research work was able to achieve accuracy that satisfied well enough.

REFERENCES

[1] M. PRASTAWA, “A brain tumor segmentation framework based on outlier detection*1,” *Medical Image Analysis*, vol. 8, no. 3, pp. 275–283, 2004.

[2] J. J. Corso, E. Sharon, S. Dube, S. El-Saden, U. Sinha, and A. Yuille, “Efficient Multilevel Brain Tumor segmentation with integrated Bayesian Model Classification,” *IEEE Transactions on Medical Imaging*, vol. 27, no. 5, pp. 629–640, 2008.

[3] X. Zhou, X. Li, K. Hu, Y. Zhang, Z. Chen, and X. Gao, “ERV-net: An efficient 3D residual neural network for brain tumor segmentation,” *Expert Systems with Applications*, vol. 170, p. 114566, 2021.

[4] E. Abdel-Maksoud, M. Elmogy, and R. Al-Awadi, “Brain tumor segmentation based on a hybrid clustering technique,” *Egyptian Informatics Journal*, vol. 16, no. 1, pp. 71–81, 2015.

[5] J. Zhang, J. Zeng, P. Qin, and L. Zhao, “Brain tumor segmentation of multi-modality MR images via triple intersecting U-Nets,” *Neurocomputing*, vol. 421, pp. 195–209, 2021.

[6] M. I. Sharif, J. P. Li, J. Amin, and A. Sharif, “An improved framework for brain tumor analysis using MRI based on yolov2 and Convolutional Neural Network,” *Complex & Intelligent Systems*, 2021.

[7] M. PRASTAWA, “A brain tumor segmentation framework based on outlier detection*1,” *Medical Image Analysis*, vol. 8, no. 3, pp. 275–283, 2004.

[8] S. Krishnakumar and K. Manivannan, “Retracted article: Effective segmentation and classification of brain tumor using rough K means algorithm and multi kernel SVM in Mr Images,” *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, no. 6, pp. 6751–6760, 2020.

[9] F. J. Díaz-Pernas, M. Martínez-Zarzuela, M. Antón-Rodríguez, and D. González-Ortega, “A deep learning approach for Brain Tumor Classification and segmentation using a multiscale convolutional neural network,” *Healthcare*, vol. 9, no. 2, p. 153, 2021.

[10] H. Habib, R. Amin, B. Ahmed, and A. Hannan, “Hybrid algorithms for brain tumor segmentation, classification and feature extraction,” *Journal of Ambient Intelligence and Humanized Computing*, vol. 13, no. 5, pp. 2763–2784, 2021.

[11] M. U. Rehman, S. B. Cho, J. Kim, and K. T. Chong, “BRAINSEG-Net: Brain tumor mr image segmentation via enhanced encoder–decoder network,” *Diagnostics*, vol. 11, no. 2, p. 169, 2021.

[12] H. Huang, G. Yang, W. Zhang, X. Xu, W. Yang, W. Jiang, and X. Lai, “A deep multi-task learning framework for Brain Tumor Segmentation,” *Frontiers in Oncology*, vol. 11, 2021.

[13] S. Ghosh, A. Chaki, and K. C. Santosh, “Improved U-net architecture with VGG-16 for brain tumor segmentation,” *Physical and Engineering Sciences in Medicine*, vol. 44, no. 3, pp. 703–712, 2021.

[14] G. Wang, W. Li, S. Ourselin, and T. Vercauteren, “Automatic brain tumor segmentation using cascaded anisotropic convolutional neural networks,” *Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries*, pp. 178–190, 2018.

[15] A. Myronenko, “3D MRI brain tumor segmentation using Autoencoder regularization,” *Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries*, pp. 311–320, 2019.

[16] G. Kim, “Brain tumor segmentation using deep fully convolutional neural networks,” *Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries*, pp. 344–357, 2018.

[17] Z. Sobhaninia, S. Rezaei, A. Noroozi, M. Ahmadi, H. Zarrabi, N. Karimi, A. Emami, and S. Samavi, “Brain Tumor Segmentation Using Deep Learning by Type Specific Sorting of Images,” *Computer Vision and Pattern Recognition*, 2018.

[18] W. Wu, D. Li, J. Du, X. Gao, W. Gu, F. Zhao, X. Feng, and H. Yan, “An intelligent diagnosis method of brain MRI tumor segmentation using deep convolutional neural network and SVM algorithm,” *Computational and Mathematical Methods in Medicine*, vol. 2020, pp. 1–10, 2020.

[19] M. U. Akram and A. Usman, “Computer aided system for Brain Tumor Detection and segmentation,” *International Conference on Computer Networks and Information Technology*, 2011.

[20] H. Dong, G. Yang, F. Liu, Y. Mo, and Y. Guo, “Automatic brain tumor detection and segmentation using U-Net based fully convolutional networks,” *Communications in Computer and Information Science*, pp. 506–517, 2017.

[21] N. Varuna Shree and T. N. Kumar, “Identification and classification of brain tumor MRI images with feature extraction using DWT and Probabilistic Neural Network,” *Brain Informatics*, vol. 5, no. 1, pp. 23–30, 2018.

[22] S. Bhuvaji, S. Dedge, P. Bhumkar, and A. Kadam, “Brain tumor classification (MRI),” *Kaggle*, 24-May-2020. [Online]. Available: https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri?select=Testing. [Accessed: 05-Nov-2022].

[23] W. Ayadi, W. Elhamzi, I. Charfi, and M. Atri, “Deep CNN for Brain Tumor Classification,” *Neural Processing Letters*, vol. 53, no. 1, pp. 671–700, 2021.

[24] J. Seetha and S. S. Raja, “Brain tumor classification using Convolutional Neural Networks,” *Biomedical and Pharmacology Journal*, vol. 11, no. 3, pp. 1457–1461, 2018.

Multiclass Brain Tumor Recognition using Convolution Neural Network

ORIGINALITY REPORT

20%	14%	11%	6%
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	2%
3	link.springer.com Internet Source	1%
4	Submitted to Liverpool John Moores University Student Paper	1%
5	www.hindawi.com Internet Source	1%
6	Xinyu Zhou, Xuanya Li, Kai Hu, Yuan Zhang, Zhineng Chen, Xieping Gao. "ERV-Net: An Efficient 3D Residual Neural Network for Brain Tumor Segmentation", Expert Systems with Applications, 2021 Publication	1%
7	Submitted to Asia Pacific University College of Technology and Innovation (UCTI)	1%