Deep Learning Towards Multi-Classification of Tumors in Brain

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

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APPROVAL

This Project titled **"Deep Learning Towards Multi-Classification of Tumors in Brain"**, submitted by Labeed Jafar Osman, ID No: 183-15-11848 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 Bachelor of Science in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 14th September 2022.

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DECLARATION

By signing this document, we certify that we completed this project under the direction of **Md. Jueal Mia, Assistant Professor, Department of CSE** Daffodil International University.Additionally, we certify that no portion of this project or any element of it has been submitted to another institution for the purpose of receiving a degree or certification.

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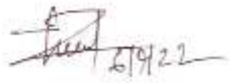

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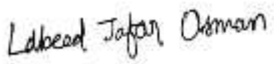

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ABSTRACT

Brain tumors are recognized as one of the most deadly malformations because of its persistent effects on the brain and consequent impact on the patient's overall wellbeing. Early detection of the brain tumors is prerequisite in order to take proper treatment in due time to safeguard the valuable life of a patient. Classification and segmentation are essential for examining tumors and preferring treatments based on the types and the shape and the size of the brain tumors. Magnetic resonance Imaging (MRI) is used because of its superior quality from which the shape, size, structure, types and soft tissues of brain tumors can be easily determined. In recent times, deep learning models for recognizing brain tumors have earned a considerable interest. As a result, the CNN architecture has received the greatest deployment out of all of these deep learning models due to its extensive capabilities and adaptability. In our work, we utilized the pretrained VGG19 architecture for the classification of tumors in brain. The Unet architecture which is based on CNN is considered to be specially created for segmenting medical images.For determining the structure, shape and size of the brain tumor. Two distinct datasets have been employed for classification and segmentation tasks during the training and testing of both models. The segmentation dataset contains MRI pictures with LGG(low grade glioma), whereas the classification dataset contains four categories of brain MRI images including meningioma, glioma, no tumor and pituitary tumor. The classification architecture generates an accuracy of 92.8% and the segmentation model creates the predicted mask of the corresponding four forms of brain MRI images

LIST OF ABBREVIATIONS

CNN	Convolutional Neural Network
MRI	Magnetic Resonance Imaging
GAN	Generative Adversarial Network
LGG	Low Grade Glioma
SVM	Support Vector Machine
DWT	Discrete Wavelet Transform
PCA	Principal Component Analysis
GLCM	Gray Level Co-Occurrence Matrix
KELM	Kernel Extreme Learning Machines
ROI	Region of Interest
MS	Multiple Sclerosis
CBIR	Content-Based Image Retrieval
PSO	Particle Swarm Optimization
DRLBP	Dominate Rotate LBP
RFE	Recursive Feature Elimination
BoW	Bag-of-Words

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CHAPTER 1
Introduction

1.1 Overview

This chapter comes up with an illustration of the background studies and information related to brain tumors and our motivation for this work, related research questions and expected output associated with the work.

1.2 Introduction

An accumulation of aberrant brain cells is known as a brain tumor. Any portion of the brain or skull can develop a brain tumor, including the brain's protective coating, the base of the skull, , the sinuses, the nasal cavity, the brainstem and many other places[11]. Depending on the tissue from which they originate, the brain can develop any one of more than 120 distinct tumor forms [12].Due to its persistent effects on the brain and subsequent effects on a patient's general health, it is recognized as one of the most perilous diseases.Around 308, 102 people are reported to have been diagnosed with a spinal cord or primary brain tumor diagnosis worldwide in 2020 [13]. Early diagnosis and categorizationthe tumor in brain is indispensable in order to take proper treatment in due time to save the life of a patient.Because of this, the identification and categorization of brain tumors has emerged as a crucial area for research in the field of biomedical engineering. Brain tumors can be benign or malignant depending on the brain cell abnormality [14]. Benign brain tumors may not cause cancer but malignant tumors may cause cancer which spread very rapidly and cause adverse conditions. The gliomas develop from glial cells, are the most frequently diagnosed and prevalent types of brain tumors. They can be classified as the grade I, grade II, grade III and grade IV depending on the risk factors and affects. The meningiomas form in the central nervous system, are another kind of frequent brain tumor.The pituitary tumors originate in the pituitary glands which regulate the hormones [15]. With the advancing technologies of computers, totally automated detection and classification is a blessing for taking impromptu and accurate decisions by the specialists. This will eventually increase the diagnostic rate and reduce the time for diagnosis.

Recently, deep learning models for classifying tumors in brain have been studied. The Convolutional Neural Network has garnered the most attention among these deep learning models because to its great performance and adaptability.The CNN model executes feature extraction and classification through the proposed various trainable layers which can be increased or decreased regarding the resultant performance Regarding these factors, we are encouraged to employ the pretrained VGG19 network, a CNN architecture, to detect and categorize brain tumors under four categories: meningioma, glioma, no tumor, and pituitary tumor. MRI images of brain tumors are used as the datasets for its high quality and non-ionizing radiation properties[16]. To determine the structure, shape and size of the tumor, segmentation is performed through the Unet architecture.

1.3 Motivation

Over the past few years, deep learning models for classifying brain tumors have been extensively researched. The CNN architecture has been used the most frequently among several deep learning models due to its great performance and adaptability. The proposed multiple trainable layers used by the CNN model to accomplish feature extraction and classification can be increased or decreased depending on the performance. Regarding these factors, we are urged to use the pretrained VGG19 architecture for categorizing brain tumors. Due to the excellent quality and lack of ionizing radiation, the datasets containing MRI images of brain tumors are used. Manual segmentation is the standard procedure for segmenting tumor although it is expensive and time-intensive. For segmenting the tumor sections, we employed a Unet architecture, which is also based on CNN and provides segmented tumor areas for MRIs.

1.4 Research Questions

- What is brain tumor?
- How can brain tumors be life threatening?
- Can deep learning models detect the brain tumor early and accurately?
- How computer aided technologies support the medical professionals to perceive the types, size, shape and position of the tumor in brain effectively?
- Why is automated brain tumor detection and classification important?

1.5 Expected Output

Brain tumor classification and segmentation procedures are essential for the early detection of different kinds of tumor with the structure, shape and size of the tumor. For the classification task, we employed the pretrained deep learning VGG19 model and for the segmentation task, the Unet architecture is implemented. We have used two distinct datasets for both the tasks. The classification dataset includes four kinds of tumor namely meningioma, glioma, no tumor and pituitary tumor. So, it is expected that the classification model will be able to classify four classes of tumor accurately with high accuracy. On the other hand, the segmentation model is expected to generate the accurate predicted mask for all the corresponding four classes of tumor.

1.6 Layout of the Report

The remaining of the report is divided into the following sections:

CHAPTER 2: Background Studies

This chapter discusses the related research works, scope of the problem and challenges.

CHAPTER 3: Research Methodology

This chapter describes the system architecture and methodology for both classification and segmentation models.

CHAPTER 4: Experimental Results and Discussion

This chapter provides the detailed result analysis and discussion for both the models.

CHAPTER 5: Conclusion and Future Scope

Finally this chapter concludes with a discussion on the future.

1.7 Summary

This chapter includes full background research, the motivation for undertaking this work, research questions and expected output in our work. The report layout is mentioned at the end.

CHAPTER 2
Background Studies

2.1 Overview
In this chapter, the most significant elements of the previous works of the researchers on the subject are summarized and scope of the problem and challenges in our work are also drawn

2.2 Related Research Works
Due to its importance in identifying tumors at an early stage, brain tumor detection and categorization has grown in popularity. This subject has been the subject of numerous studies. The deep neural network has experienced tremendous growth in popularity because of its excellent effectiveness in identifying brain tumors. Research studies related to deep CNN architecture are worth mentioning for this reason. There are also some notable GAN based research works related to this subject. Some of them are mentioned here with concise descriptions.

In the paper by Ismael et al., they combined the statistical traits obtained from the 2D DWT and 2D Gabor extraction methods independently for feature extraction [17]. The features were given to a conventional neural network trained by backpropagation in order to categorize three different tumor types such as meningioma, glioma, and pituitary tumors.

In a particular study using CNN architecture, Sultan et al. suggested a technique for classifying MRI images of brain tumors into three distinct categories: meningioma, glioma, and pituitary tumor. It is also effective at differentiating gliomas into various grades, such as grade II, grade III, and grade IV [18]. However, a dataset with greater number of MRI images required to be utilized to assess the proposed approach.

Naceur et al. applied deep learning models called 2CNet, 3Cnet, and EnsembleNet utilizing their suggested training technique in order to create an autonomous incremental convolutional neural network [19]. The EnsembleNet is a combined 2CNet and 3Cnet model that incorporates ensemble learning. The suggested model has to be validated using large-scale datasets.

Havaei et al. introduced a novel technique that makes use of CNN architecture in their paper. Their CNN architecture is a two-path architecture that can simultaneously extract local features from the MRI of the brain tumors and global features from the context of those features [20]. The CNN base output, which is then fed back into the CNN, has been taken into consideration when training the architecture using the two-phase training method. To effectively handle a large volume of MRI images, the architecture must, however, be observed on large datasets.

Since the surrounding tumor tissues can provide extra information about the tumor, Cheng et al. applied the enhanced tumor portion as the ROI rather than the actual tumor region and divided it into ring-shaped subregions to keep the spatial information. To identify and categorize three kinds of tumors, including meningioma, glioma and pituitary tumors, they used GLCM (Gray Level Co-occurrence Matrix), intensity histograms, and BoW (bag-of-words) approaches as feature extraction methods. They also combined SVM with the HIK kernel [21].

In another paper by Cheng et al., brain tumors are being identified from T1-CE MRI images utilizing the CBIR (Content-based image retrieval) approach In order to implement the information from the surrounding tumor tissue, they first improved the tumor portion to be used as the ROI. Using the adaptive spatial pooling approach, the ROI was subsequently divided into small regions based on intensity orders. In order to create the final feature, they aggregate the local features on each subregion using the Fisher Vector technique after extracting them as raw picture patches from each subregion [22].

Using two databases combined with a four evaluating strategy and a two 10 cross validation approach, Milica M. Badza and Marko C. Barjaktarovic proposed a novel and straightforward CNN approach. 10 fold cross validation for both the subject-wise and the record-wise approaches have been utilized on both the original and the augmented photos to test the model [23]. The augmented images produced by record-wise cross validation yield the best results. The method uses the entire set of MRI images without any pre-processing.

Pashaei et al.proposed an approach that extracts brain tumor features using CNN and subsequently classifies the obtained features into three kinds of tumors namely pituitary tumors, glioma and meningioma using KELM (Kernel Extreme Learning Machines) (Kernel Extreme Learning Machines) [24].

Deep neural network classifiers were used by Mohsen et al. in conjunction with principal component analysis, discrete wavelet transform and classifications for normal, sarcoma, glioblastoma and metastatic bronchogenic carcinoma tumors to categorize brain tumors into four unique groups [25]. Although this methodology's architecture mirrored that of conventional convolutional neural networks (CNN), it produced superior accuracy results.

ResNet50 architecture, one of the CNN architectures, was employed for the classification of brain tumors by Ahmet Cinar and Muhammed Yildirim. However, they have altered the ResNet50 architecture by substituting 10 layers for the final 5 layers. Their altered architecture can only classify brain tumors binarily [26].

Afshar et al. used a capsule network on segmented tumor regions to overcome CNN's drawbacks, which included losing the active features at a specific location in the subsampling layers and getting subpar training results with little datasets [27]. To achieve higher accuracy, segmented tumor portions must be sent to CapsNet, which takes time.

In another work, CapsNet was established by Afshar et al. in which they use whole-brain MRI as input without the requirement to section the tumor. It can preserve spatial information[28]. However, the coarse tumor boundary is also shown in order to draw greater attention to the primary target.

Convolutional neural networks were used by Halimeh Siar and Mohammad Teshnehlab to concurrently detect brain tumors and MS (Multiple Sclerosis) [29].

On several datasets, Tahir et al. showed how different combinations of noise reduction, contrast enhancement, and edge enhancement preprocessing techniques can increase the outcomes of segmentation and classification. They used SVM for binary classification and the Otsu method for pixel-based picture segmentation [30].

Sharif et al. employed the pre-trained Inception v3 architecture to extract features.The extracted features were then combined with DRLBP (Dominate Rotate LBP) for enhanced texture analysis. To categorize brain tumors, the feature vectors are improved using the algorithm of PSO (Particle Swarm Optimizer) and the softmax classifier [31].

Block-wise VGG16 networks focused on transfer learning was used by Swati et al. The model underwent a minimal amount of preprocessing and handcrafted features were not employed [32]. The model's output was contrasted with both deep learning and conventional machine learningmethods.

In the method suggested by Sajjad et al. to categorize the multiple graded tumors in brain a brain tumor segmentation method was applied, followed by an intensive data augmentation strategy. The segments of the brain tumor were created using a CNN model.Because of the small scale datasets, eight distinct types of data augmentation strategies, including various geometric transformations and noise invariances, have been applied to enhance the segmented data. The pretrained VGG19 architecture has finally processed data for classification [33].

Using the Inception-v3 and DenseNet201 architectures, Noreen et al. constructed two different multi-level architectures. In these pre-trained architectures, features are concatenated after being taken from different modules and sent into the softmax layer for classification. Fine-tuned techniques on pre-trained architecture could not be used in their suggested model [34].

The study by Chelghoum et al. on several pre-trained CNNs used a small scale dataset. For comparative analysis in the context of transfer learning, the study makes use of nine pre-trained CNN architectures: AlexNet, ResNet18, ResNet50, VGG16, VGG19,SENet GoogleNet, ResNet101 and Inception-ResNet-v2 [35].

According to Togacer et al., high classification performance can be produced by combining cutting-edge methods like the RFE (Recursive Feature Elimination),hypercolumn technique and SVM with pretrained VGG16 and AlexNet architectures. The proposed model takes advantage of the generalization capabilities of these two architectures by merging the deep characteristics generated from the layers that are fully connected [36]. The suggested model can only be utilized for binary classification; however, in order to categorize different tumors, a sizable dataset must be given into the model, which can be a challenging and time-consuming operation.

A pretrained CNN network is adjusted in a GAN model proposed by Ghassemi et al. to serve as a classifier for the classification of tumors in brain and a deep CNN is applied as the discriminator for detecting the fraudulent images that are generated by the generative model [37]. Due to several GAN restrictions, which prevent the use of a few effective architectures as the discriminator since the bigger input size is a requirement as the MRI input size in the proposed model was 64 × 64.

Rezaei et al. developed a cGAN approach for segmenting the total tumor area, the core tumor area, and the augmenting tumor area into three unique subregions with various labels, which are then utilized to forecast the patient's survival days following tumor detection. Their model acquired a loss that enables it to operate effectively on unobserved data [38].

2.3 Research Summary

Several studies have been conducted to identify and classify brain tumors using automated computer aided methods keeping in mind that early diagnosis can support the medical professionals to provide impromptu treatment and medication to the brain tumor affected patients. Due to its excellent effectiveness in identifying brain cancers, the deep neural network has experienced tremendous growth in popularity. For this reason, research in relation to deep CNN architecture is important. There are also some noteworthy GAN-based published studies on this topic.

2.4 Scope of the Problem

Most research studies have concentrated on classifying tumors into two or three distinctive types or classifying them binarily. The pretrained VGG19 model on classifying tumors of four types including meningioma, glioma, no tumor and pituitary tumor is being utilized. The segmentation of MRIs is essential since only the classification model cannot provide the information on the structure, size or shape of the tumors although the majority of research focuses on classifying tumors rather than segmenting the tumors. Unet model for the purpose of segmenting tumor regions from the MRI image has been used. Existing models work well with small datasets for classifying a variety of tumors however performance decreases as dataset size increases. The volume of the dataset has been expanded forthe enhancement of performance to tackle the issue of a limited dataset.

2.5 Challenges

There are more than 120 different forms of tumors, the most of which are fatal. [12]. We used the pretrained VGG19 model for categorizing tumors into only four classes. Other classes of brain tumors could not be classified due to unavailability of datasets containing other types.

Moreover, datasets that can be found have small instances of images. Segmentation of brain tumors is important to identify the tumor size, shape and structure. There is also a lack of dataset regarding segmentation. For segmentation, a dataset with brain MRI images with corresponding mask is required to train the model. Availability of such datasets is tough let alone getting datasets for segmentation for other kinds of tumors. As a result, manual segmentation is required to be done to make a dataset for segmentation which is time consuming and tiring.

2.6 Summary

In this chapter, the research summary is concisely discussed with related scope of the problem and challenges in our work.

CHAPTER 3
Research Methodology

3.1 Overview

This chapter provides an overview of the datasets utilized in this research, data preprocessing operations such dataset augmentation, model architectures for both classification and segmentation, and a brief explanation of how the models for segmentation and classification function.

3.2 Datasets

In our work, we have utilised two datasets for categorizing tumors in brain and segmentation. The first dataset is applied for classifying four forms of tumors including meningioma, glioma, no tumor and pituitary tumor [1] and the second dataset is used to separate the tumors from the MRI images to perceive the appearance of the classified tumors [2].

3.2.1 Dataset for Classification

The classification dataset is obtained from Kaggle which contains a total of 7023 brain MRI (Magnetic Resonance Imaging) images [1]. The dataset combines the Figshare dataset, the Br35H dataset andthe SARTAJ dataset. Two directories are included, one for testing and the other for training. The training and testing folder further have four folders for four distinctive tumors namely meningioma, glioma, no tumor and pituitary tumor. Number of MRI images in the training folder : no tumor (1595 images), glioma (1321 images), meningioma (1339 images) and pituitary tumor (1457 images) and number of MRI images in the testing folder: no tumor (405 images), glioma (300 images), meningioma (306 images) and pituitary tumor (300 images). The three different forms of brain tumors in the Figshare Dataset are meningioma (708 slices), glioma (1426 sections), and pituitary tumor (930 slices). represented obtained from 233 brain tumor patients includes 3064 MRI images which are T1-weighted contrast-enhanced [3]. The SARTAJ dataset contains 3264 MRI brain images of four kinds of brain tumor namely meningioma, glioma, no tumor and pituitary tumor [4]. This dataset includes no tumor 1500 MRI images from the Br35H dataset that contains [5].

Table 3.1: Figshare Brain Tumor Dataset

Tumor Class	Number of Slices
Glioma	1426
Meningioma	708
Pituitary Tumor	930
Total number of images	3064

Table 3.2: SARTAJ Brain Tumor Dataset

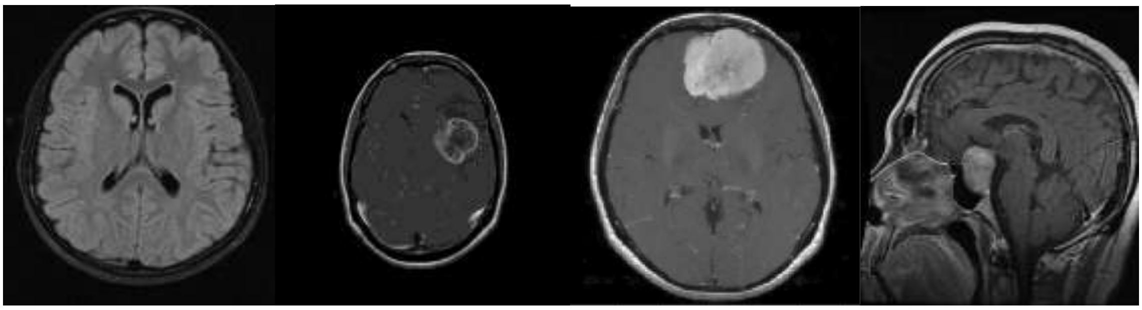
Tumor Class	Training	Testing	Number of MRI Images
No Tumor	395	105	500
Glioma	826	100	926
Meningioma	822	115	937
Pituitary Tumor	827	74	901
Total number of images			3264

Table 3.3: Combined Classification Dataset of Brain MRI Images

Tumor Class	Training	Testing	Number of MRI Images
No Tumor	1595	405	2000
Glioma	1321	300	1621
Meningioma	1339	306	1645
Pituitary Tumor	1457	300	1757
Total number of images in the classification dataset			7023

3.2.1.1 Format of Classification Dataset

Images from the combined classification dataset are in the JPG format. The dataset contains images of various sizes. So, all the MRI images have to be resized to same size for classification of brain tumors. Figure 3.1 depicts four classes of brain MRI tumors for classification.



(a) No Tumor (b) Glioma (c) Meningioma (d) Pituitary Tumor

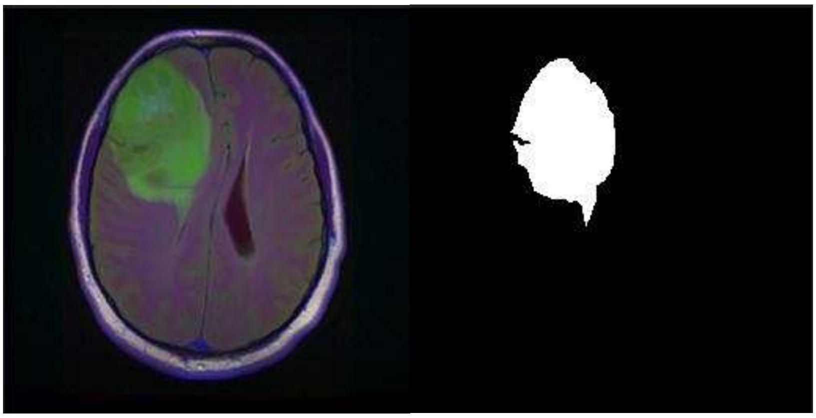
Figure 3.1: MRI brain tumor image sample from classification dataset including (a) No Tumor, (b) Glioma, (c) Meningioma and (d) Pituitary Tumor

3.2.2 Dataset for Segmentation

The segmentation dataset includes FLAIR abnormality segmentation masks corresponding to brain MRI images and is available in Kaggle [2]. Mateusz Buda performed manual segmentation on FLAIR MRI images acquired from the TCIA (The Cancer Imaging Archive). These MRI images belong to 110 patients who have been part of the LGG (low grade glioma) collection of the TCGA(The Cancer Genome Atlas). The collection has 3929 MRI images altogether that represent low grade glioma in 1373 images and no tumor in 2556 images. This dataset is used in the paper by Mateusz Buda [6] and by Mazurowski et al. [7].

3.2.2.1 Format of Segmentation Dataset

The segmentation dataset contains images that are 256 by 256 pixels in size and are in the TIFF format. Figure 3.2 depicts the brain MRI images with corresponding masked images.



(a) Brain MRI Image (b) Corresponding Segmented Mask

Figure 3.2 MRI brain tumor image sample from segmentation dataset

3.3 Preprocessing

Resizing and augmentation of the original classification dataset is discussed in this section.

3.3.1 Resize

The dataset for classification contains 7023 MRI brain images with different sizes. So to balance the size, the images were resized to 256 by 256 pixels for classification.

3.3.2 Augmentation

Data augmentation improves the performance and output of deep learning models by adding new and different samples to training and testing datasets. If the dataset is substantial and adequate, a deep learning model operates more effectively and is more accurate. The classification dataset contains two directories of four distinctive tumors like meningioma, glioma, no tumor and pituitary tumor each. The training and testing directories do not contain a similar number of images in each folder. As a result, all the folders in both the directories need to be balanced for classification. In order to balance the dataset and preserve the brain tumor in the MRI images, augmentation techniques such rotation, width shifting, height shifting, zooming, and horizontal flipping were applied and Figure 3.3 depicts the applied augmentation technique.

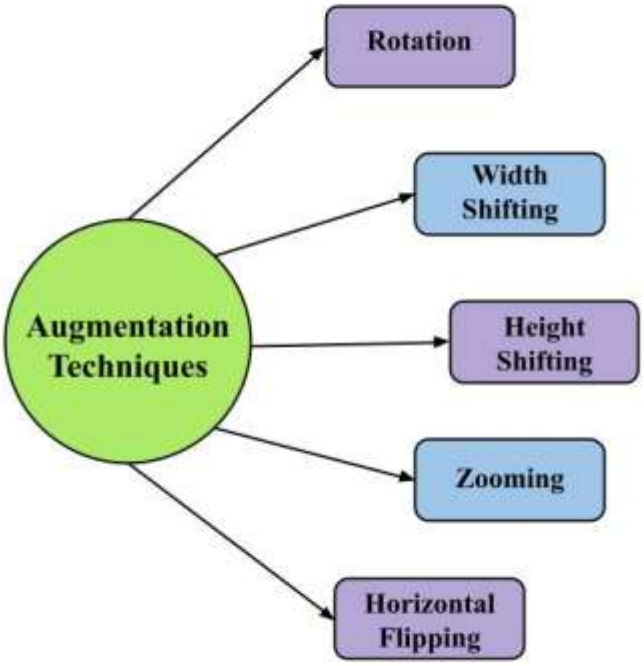


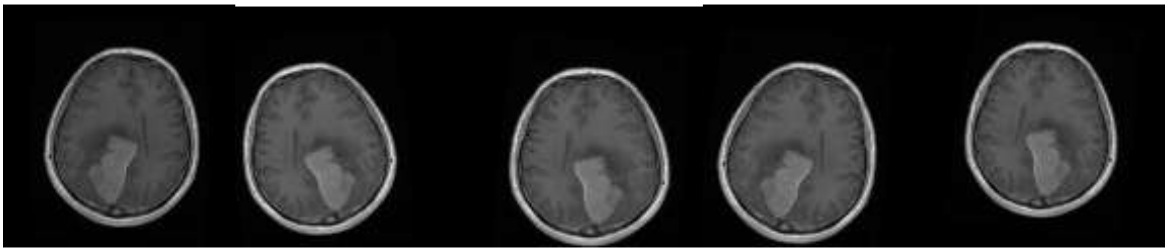
Figure 3.3 Applied augmentation techniques

After performing augmentation, the training directory has 5000 images and the testing directory has 1000 images in each of four types of tumors. So the total number of images after applying augmentation is 24000 with 20000 training and 4000 testing images. The augmentation has been done such that the training directory has 80% of the images and the testing directory has 20% images. After applying augmentation, the number of images in each folder of the two directories is shown in Table 3.4.

Table 3.4: Number of images after applying augmentation

Tumor Class	Training	Testing	Number of MRI Images
No Tumor	5000	1000	6000
Glioma	5000	1000	6000
Meningioma	5000	1000	6000
Pituitary Tumor	5000	1000	6000
Total number of images after augmentation			24000

In the following, Figure 3.4 depicts one of the original images with four corresponding augmented images after performing augmentation in the four categories of tumors to make the dataset robust.



(a) (b) (c) (d) (e)

Figure 3.4: (a) image before augmentation and (b-e) augmented MRI brain tumor images after dataset augmentation

3.4 Workflow of the Entire System Architecture

The following Figure 3.5 illustrates the workflow of the entire system.

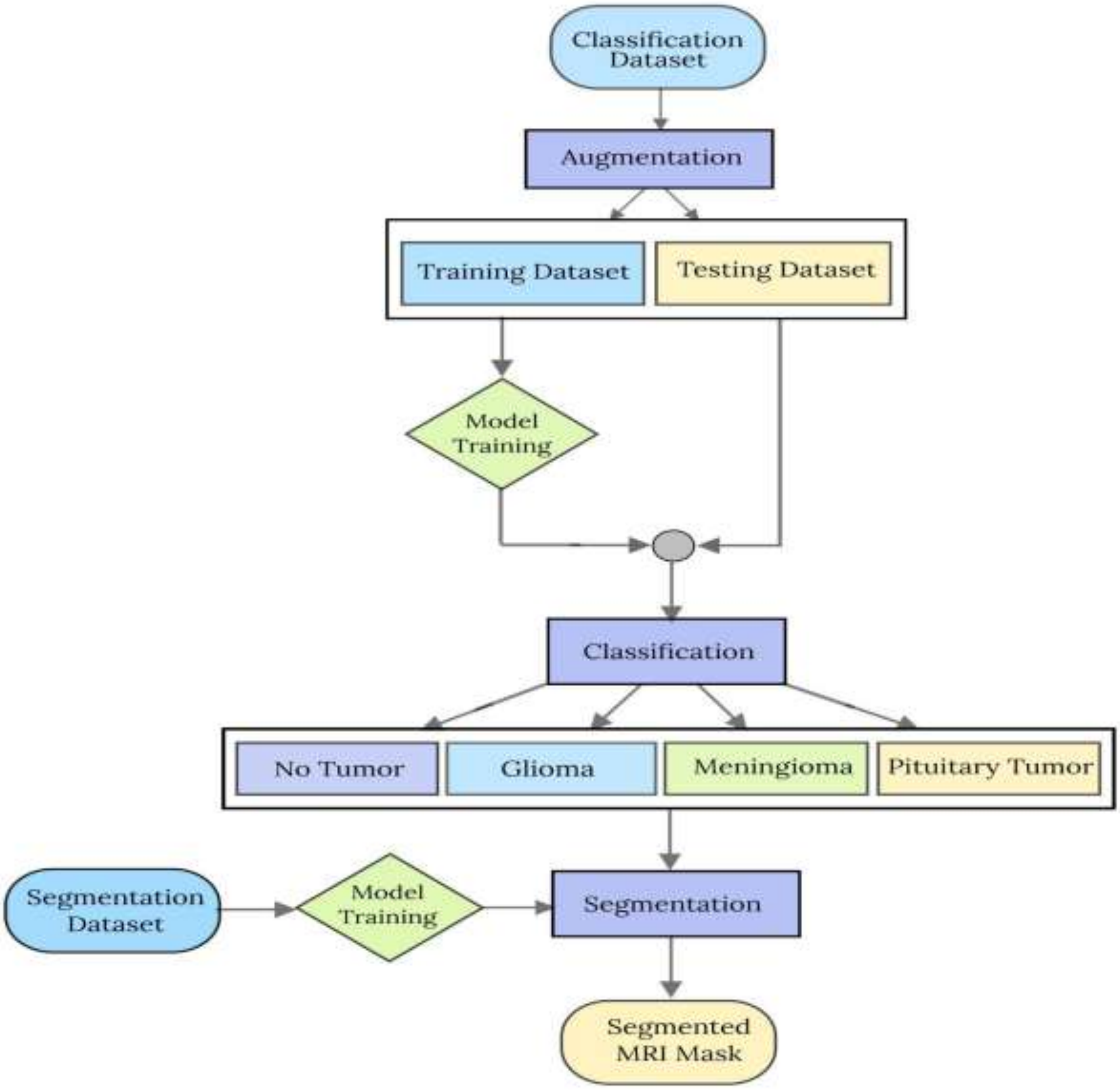


Figure 3.5: Workflow of the entire system

The workflow described above includes the following steps. Four different forms of tumors, including meningioma, glioma, no tumor and pituitary tumor are included in the dataset of classification. The training and testing directories of this dataset each have four folders that contain four different types of tumors. In order to enhance the classification model performance and generate better outcomes, the training and testing directories containing datasets are then augmented. The classification model is subsequently trained to learn about features using the augmented training dataset. Four different types of tumors are categorised using a fine-tuned classification model after learning the features of the brain MRI image. At last, the augmented testing dataset is used to test the model to determine whether it can identify the tumor type and generate the accurate result. After classification, a segmentation process is performed for segmenting the tumor portion from the MRI image of brain. Segmentation dataset is used for this purpose. The segmentation dataset contains brain MRI images with LGG (low grade glioma) with corresponding mask which is employed to train the model for segmentation. After training the model, images from the classification dataset are fed into the segmentation model for segmenting four types of tumors to perceive the size and shape of the respective segmented tumors from MRI.

3.5 Architecture of the Entire System

The below Figure 3.6 illustrates the entire system architecture for classification and segmentation of four types of tumor in the human brain.

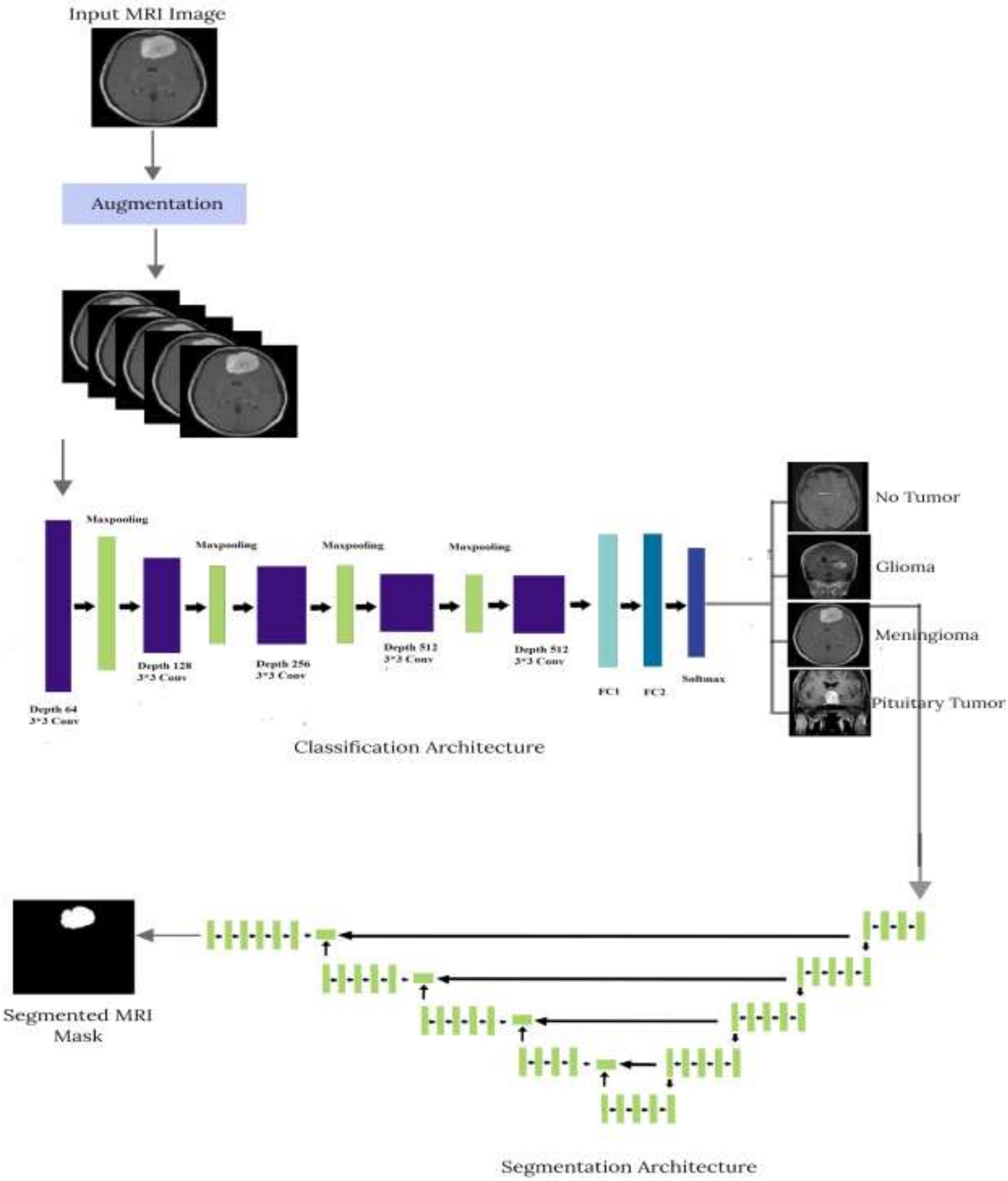


Figure 3.6: Architecture of entire system

Four different types of MRI images of brain are initially given to the system as input. Then the images are augmented to enhance the dataset for helping the classification model perform better. The augmented images from four classes are sent into the VGG19 model used for classification of tumors into four distinctive classes. After classification, each MRI image from the distinctive class is segmented by feeding the images into the Unet segmentation model to generate the tumor size and the shape of the particular brain MRI image.

3.5.1 Architecture of Classification Model

Millions of images from the image database, ImageNet, are used to train the VGG19 model which is a Convolutional Neural Network with layers of 19. Andrew Zisserman and Karen Simonyan established VGG19 architecture that uses a small 3x3 size of kernel throughout all convolutional layers to reduce the number of parameters [10]. The architecture of the VGG19 model for classifying four types of brain tumor is illustrated below in Figure 3.7.

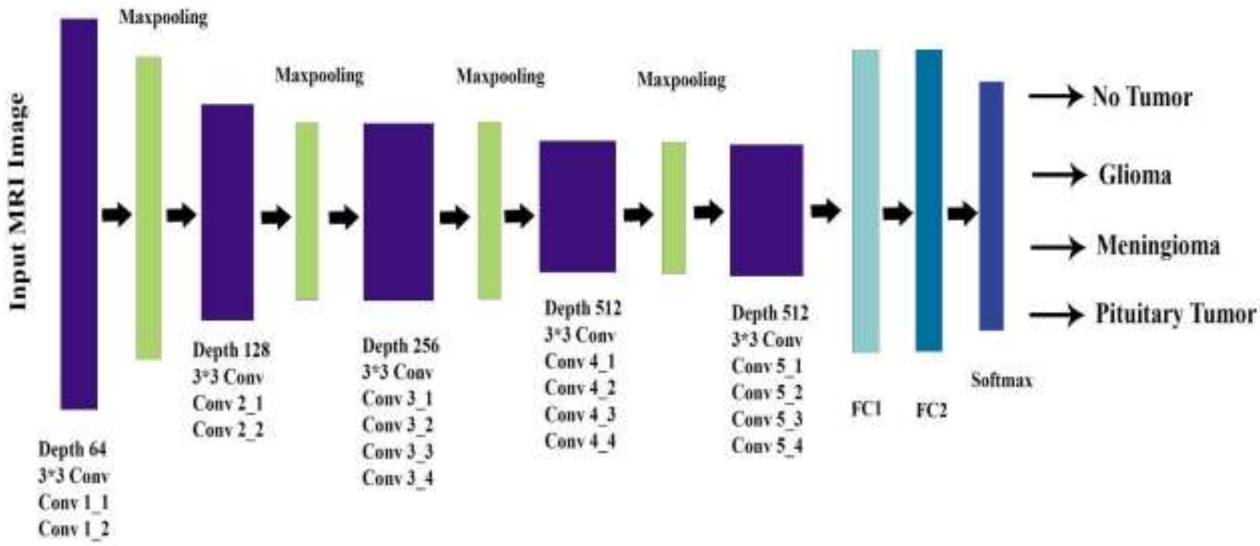


Figure 3.7: Architecture of VGG19 network for Classification

A 128x128 RGB brain MRI picture was provided to the VGG19 network as input, yielding a matrix with the dimensions 128x128x3.The only preprocessing operation was to determine the mean RGB value of each pixel across the whole training set. Using kernels along with a stride size of 1 pixel and a size of 3x3, it was possible to capture the entire image. The spatial padding was used to preserve the MRI image's spatial resolution. Max pooling was conducted using stride 2 throughout by a 2x2 pixel window. There are five maximum-pooling layers that do spatial pooling. Following this, non-linearity was introduced to the model using the Rectified Linear Unit (ReLu) to improve classification accuracy and computation time. As opposed to earlier models that used sigmoid or tanh functions, the addition of ReLu made the network perform far better. There are three fully connected layers which have a size of 4096 and the last has a size of 1000 followed by the layer named softmax for the classification of four categories of brain tumor namely: meningioma, glioma, no tumor and pituitary tumor The following Table 3.5 displays the layers of the VGG19.

Table 3.5: Layers of the classification model VGG19

Blocks	Layers	Filter Size	Depth
Block 1	Conv 1_1	3x3	64
	Conv 1_2		
	Maxpool	2x2	
Block 2	Conv 2_1	3x3	128
	Conv 2_2		
	Maxpool	2x2	
Block 3	Conv 3_1	3x3	256
	Conv 3_2		
	Conv 3_3		
	Conv 3_4		
	Maxpool	2x2	
Block 4	Conv 4_1	3x3	512
	Conv 4_2		
	Conv 4_3		

	Conv 4_4		
	Maxpool	2x2	
Block 5	Conv 5_1	3x3	512
	Conv 5_2		
	Conv 5_3		
	Conv 5_4		
	Maxpool	2x2	
Block 6	Fully Connected (FC1) - (4096)		
	Fully Connected (FC1) - (4096)		
	Softmax		

3.5.2 Architecture of Segmentation Model

The Unet which is a significant Convolutional Neural Network performs the best in segmenting images. The architecture was created by Olaf Ronneberger et al. for segmenting images pertaining to medicine [8]. The design outperformed the Ciresan et al. [9] network's performance in cell segmentation, which helped it win the ISBI cell tracking challenge 2015 by a significant margin. The following Figure 3.8 represents the Unet segmentation architecture for separating the portion of tumor from the MRI images of brain.

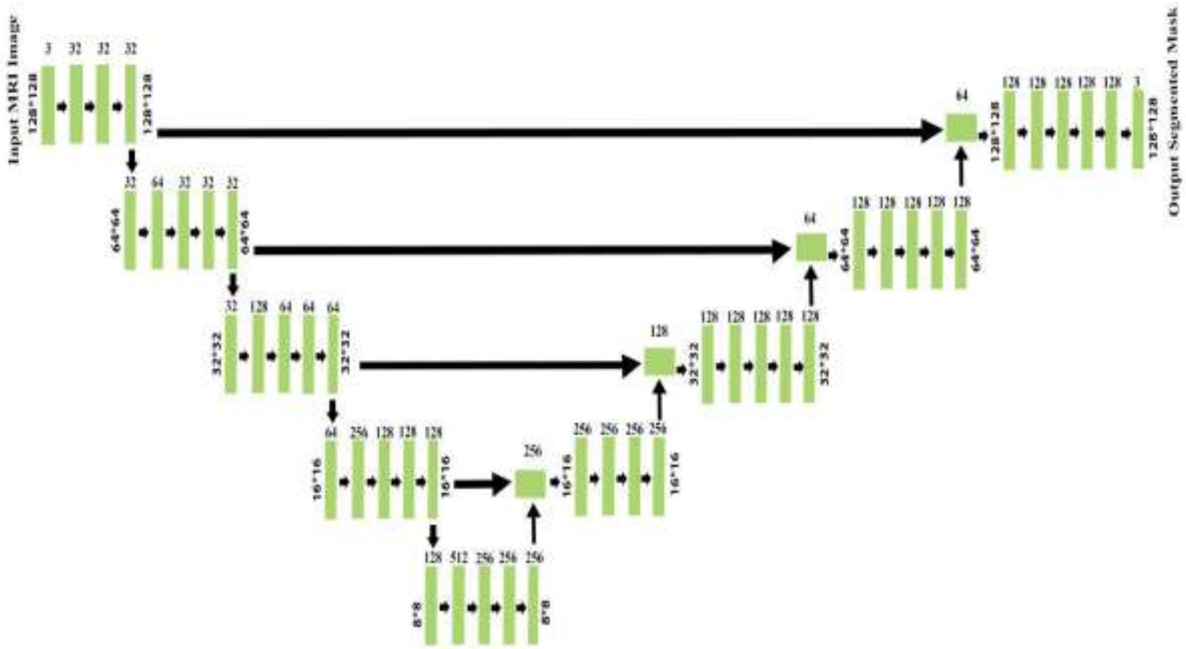


Figure 3.8: Architecture of Unet network for segmentation

The Unet architecture takes Input barin MRI image as input to segment the portion of the tumor from the brain. The architecture of Unet comprises two paths: a downsampling contraction path on the left side and an upsampling expansion path on the right side. The left side contraction path is also known as the encoder which is utilized to preserve the information of the image. Because of the downsampling and upsampling path the architecture is U shaped and hence named as Unet. The encoder is a pile of maximum pooling and convolutional layers. The decoder, also known as the right side expansion path, is used to implement and enforce localization utilizing transposed convolutions. The downsampling contraction path is in which standard convolutions and maximum pooling layers are applied. The image size steadily decreases while the depth keeps rising in the encoder between

128x128x3 and 8x8x256. It entails regularly applying two 3x3 unpadded convolutions, followed by a Rectified Linear Unit (ReLU), a 2x2 max pooling process, and a stride of 2 for downsampling.The amount of feature channels are increased by two at each stage of downsampling. The right side upsampling expansion path is where transposed convolutions in addition to traditional convolutions are applied. The image size and depth are gradually increased and decreased in the decoder between 8x8x256 and 128x128x3. The expansion path entails upsampling the features cutting the number of channels in the features in half with a 2x2 convolution, concatenating the commensurately cropped features from the contracting path and performing two 3x3 convolutions, each accompanied by a ReLU. Due to the reduction of border pixels in each convolution, cropping is required. The segmentation model generates the predicted tumor mask of the corresponding input brain MRI image

3.6 Summary

This chapter provides a summary of how the entire system detects tumors, categorizes them, and determines their size and shape.

CHAPTER 4

Experimental Results and Discussion

4.1 Overview

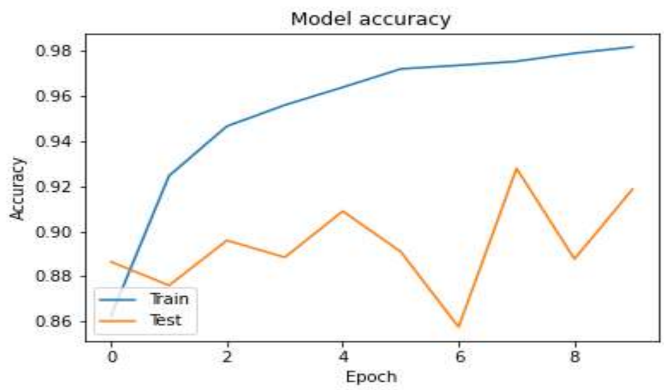
In this chapter, the results and effectiveness of the two models used for classification and segmentation are briefly discussed.

4.2 Evaluation and Analysis

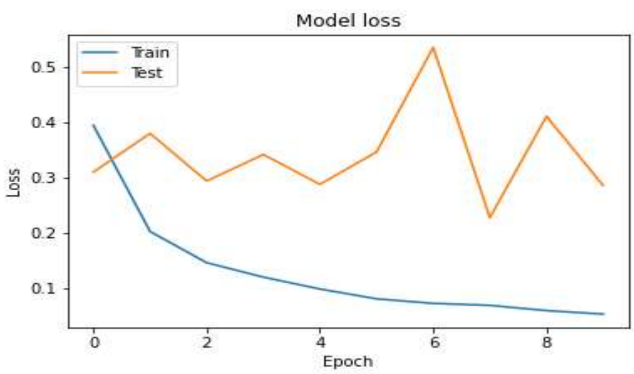
In order to reflect the performance of the respective two models, the results of the segmentation model Unet and the classification model VGG19 are reviewed and analyzed.

4.2.1 Evaluation of the Classification Model

To categorize brain MRI data into four separate classes, we applied a pretrained model of the VGG19 network. The accuracy and loss plot depicting how well the VGG19 model performed is shown in Figure 4.1.



(a) Plot for model accuracy



(b) Plot for model loss

Figure 4.1: (a) Plot for accuracy and (b) Plot for loss of the pretrained classification model VGG19 network.

The accuracy and loss plots for the pretrained architecture VGG19 for the classification task of brain tumor are shown in the aforementioned Figure 4.1, with the training phase curve and the validation phase curve in each plot. In both of the plots of the pretrained model, there are some variations between the training curve and the validation curve as we trained the model for 10 epochs. The variations can be reduced between both the curves in each plot by increasing the number of epochs for model training. The maximum training accuracy is 98.2% and the maximum validation accuracy is 92.8% of the pretrained model VGG19. The evaluation metrics addressing the classification model are showed in Table 4.1.

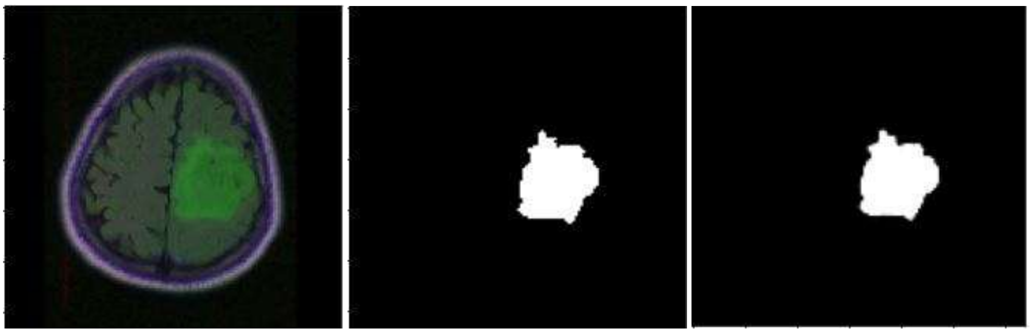
Table 4.1 Metrics for evaluation addressing the classification model VGG19

	Accuracy	Recall	Precision	TP	TN	FN	FP
Training	98.2	98.1	98.2	19650	59727	2939	2463
Validation	92.8	92.6	93	3714	11752	581	556

The above Table 4.1 illustrates the differences between the evaluation metrics regarding both the training phase and the validation phase of the pretrained model VGG19.

4.2.2 Evaluation of the Segmentation Model

The appearance and structure of the brain tumor are assessed by the segmented model Unet, which is trained employing the segmentation dataset that includes brain MRI having LGG (low grade glioma) and relevant corresponding mask. The segmentation model is trained through the dataset to predict the mask of the input MRI image. Figure 4.2 illustrates the MRI images for segmentation during training the segmentation Unet model.

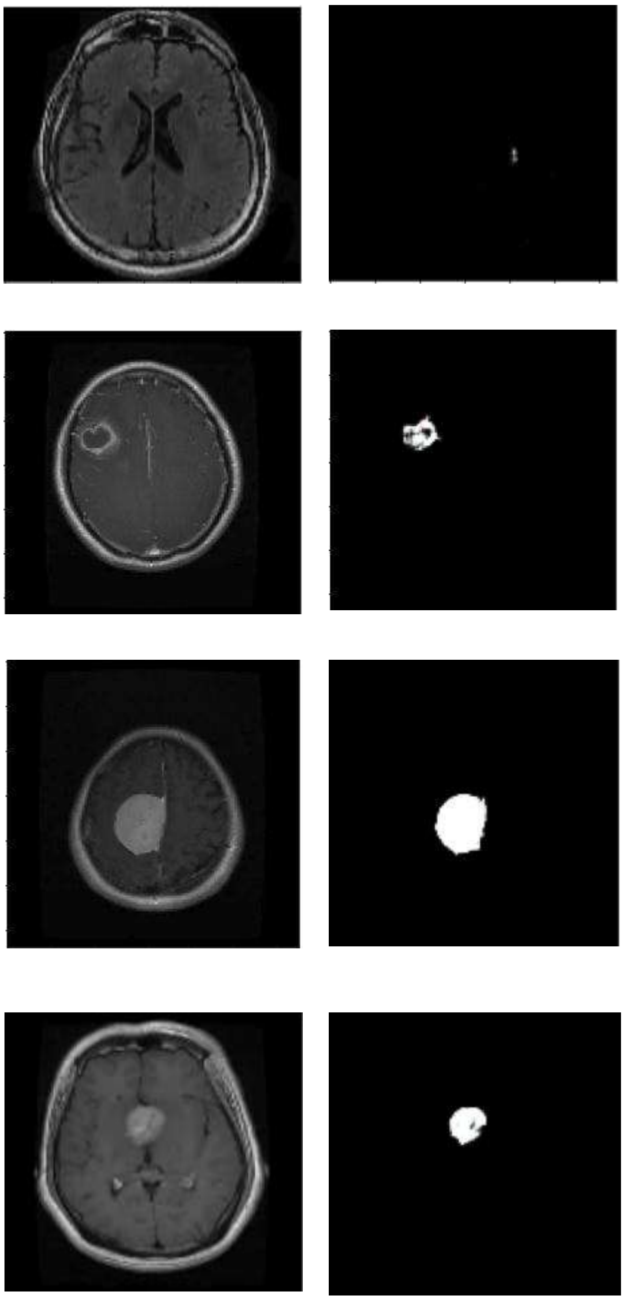


(a) MRI Image of Brain (b) Corresponding Mask (c) Prediction Mask

Figure 4.2: Generated predicted mask during training for segmentation

In Figure 4.2, an image of an MRI brain tumor with corresponding mask from segmentation dataset is represented. The prediction mask is generated while training the model. The segmented model is tested using the classification dataset to predict the corresponding mask of the four types of tumor including meningioma, glioma, no tumor and pituitary tumor.

MRI Image of Brain | Prediction Mask



No tumor

Glioma

Meningioma

Pituitary Tumor

Figure 4.3 Segmented MRI Mask of four types of tumor

Figure 4.3 illustrates the four types of tumor including meningioma, glioma, no tumor and pituitary tumor from the classification dataset with the corresponding predicted mask of the four types of tumor.

4.3 Discussion

We categorized four specific forms of tumor including meningioma, glioma, no tumor and pituitary tumor using the classification model VGG19 that shows result with accuracy of 92.8%. Then we trained the segmentation model Unet over the segmentation dataset that contains LGG (low grade glioma) to predict the corresponding mask. Finally to test the model, a classification dataset is fed to the model for generating the corresponding predicted mask of the four types of tumor.

4.4 Experimental Tools

The required hardware and software to carry out the research experiment are as follows.

Hardware

- Intel Core i7 7500U CPU (2.90GHz) with AMD Radeon R7 M440 Graphics card and 16GB RAM

Software

- Open source Anaconda for distribution of Python
- Python 3.9
- Spyder IDE
- Google Colab
- Windows 10

4.5 Summary

This chapter goes into depth detail on how our classification and segmentation model performed**.**

CHAPTER 5
Conclusion and Future Scope

5.1 Conclusion

In our work, we have used two distinctive architectures for the purpose of classification and segmentation of four types of tumor. We also used two different classification and segmentation datasets for training and testing the classification and segmentation task. We used the VGG19 architecture which is a pretrained Convolutional Neural Network for classifying four classes of tumors. The most common four classifications of tumor such as meningioma, glioma, no tumor, and pituitary tumors are represented in the classification dataset which is used to train and validate the classification model.Our classification model VGG19 generates results with an accuracy of 92.8%. We employed the Unet architecture, a CNN architecture created specifically for the objective of segmenting biomedical images, for segmentation. The Unet architecture is trained over the segmentation dataset that contains brain MRI images with LGG (low grade glioma). The segmentation model generates the prediction mask related to the input MRI image from the segmentation dataset. To test the model if it can generate the accurate mask to the corresponding MRI image, the model is tested using the classification dataset. The Unet model generates the predicted mask of the brain MRI to determine the shape and the size of tumors which can be used for further research studies.

5.2 Implication of the Further Research

Classifying brain tumors is a demanding and complex problem in medical image processing. A brain tumor can form in either an adult or an infant, and it is among the most lethal and severe cancer types. A precise and prompt detection of the tumor's presence is essential for taking impromptu decisions and medications for patients having brain tumors. One of the most important steps for doctors is the adoption of computer aided approaches to diagnose brain tumors. These tools make it simpler for experts to detect different types of malignant brain tumors. Traditional approaches still have room for error, but they can be avoided. This study shows that brain tumors, which occasionally result in cancer, can be identified with MRI images. Our pretrained VGG19 model can categorise tumors into four groups namely no tumor, glioma, meningioma, and pituitary. A segmentation model is designed to segment the tumors in order to determine the tumor size and shape. This method of classification and segmentation will support medical professionals to classify tumor types precisely and segment the tumor portion to identify the form and size for potential future treatment and medication based on the seriousness of the brain tumor.

5.3 Recommendations and Future Scope

In the future, we will focus on improving our pretrained VGG19 model for classifying tumors for other various types of brain tumors including assessing various grades of glioma. It may be required to use different pre-trained CNN architecture for comparing the classification results. By training the segmentation model with more data, it may produce superior segmentation outcomes for different types of tumor. As a result, it could be necessary to create manually segmented tumor masks. For better performance to ascertain the form and size of the tumor, it can be necessary to manually segment masks from several kinds of brain MRI images.

References

[1] Brain Tumor MRI Dataset, available at https://www.kaggle.com/brain-tumor-mri-dataset, last accessed on 07- 07-2022 at 10 am

[2] Brain MRI segmentation, available at https://www.kaggle.com/datasets/mateuszbuda/lgg-mri-segmentation, last accessed on 07- 07-2022 at 11 am

[3] Figshare Brain Tumor Dataset, available at https://figshare.com/articles/dataset/brain_tumor_dataset , last accessed on 08- 07-2022 at 9 pm

[4] SARTAJ Brain MRI , available at https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri, last accessed on 08- 07-2022 at 10 pm

[5] Br35H :: Brain Tumor Detection 2020, available at https://www.kaggle.com/datasets/ahmedhamada0/brain-tumor-detection, last accessed on 08- 07-2022 at 9:30 pm

[6] M. Buda, A. Saha, M. A. Mazurowski , "Association of genomic subtypes of lower-grade gliomas with shape features automatically extracted by a deep learning algorithm", "Computers in Biology and Medicine", vol. 109, pp. 218-225, June 2019

[7] M. A. Mazurowski, K. Clark, N. M. Czarnek, P. Shamsesfandabadi, K. B. Peters, A. Saha "Radiogenomics of lower-grade glioma: algorithmically-assessed tumor shape is associated with tumor genomic subtypes and patient outcomes in a multi-institutional study with The Cancer Genome Atlas data." Journal of Neuro-Oncology, vol. 133, pp. 27-35 May 2017**,** Publisher : Springer

[8] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in International Conference on Medical image computing and computer-assisted intervention, pp. 234–241, Springer, 2015.

[9] D. Ciresan, A. Giusti, L. Gambardella, J. Schmidhuber, "Deep neural net-works segment neuronal membranes in electron microscopy images", Advances in Neural Information ProcesSing Systems, pp. 2852-2860, NeurIPS, 2012

[10] K. Simonyan, A.Zissereman, "Very Deep Convolutional Networks for Large-scale image recognition", ICLR 2015, vol. 1, May 2015

[11] National Cancer Institute, available at https://www.cancer.gov/types/brain/patient/adult-brain-treatment-pdq, last accessed at 30-07-2022 at 6pm

[12] Johns Hopkins, available at https://www.hopkinsmedicine.org/health/conditions-and-diseases/brain-tumor, last accessed at 30-07-2022 at 6: 10 pm

[13] Brain Tumor : Statistics | Cancer.Net, available at https://www.cancer.net/cancer-types/brain-tumor/statistics, last accessed at 30-07-2022 at 6: 30pm

[14] Brain Tumours - NHS, available at https://www.nhs.uk/conditions/brain-tumours/ , last accessed at 30-07-2022 at 6:38 pm

[15] Cancer Research UK, available at https://www.cancerresearchuk.org/about-cancer/brain-tumours/types, last accessed at 30-07-2022 at 7 pm

[16] T. Geva, "Magnetic Resonance Imaging: Historical Perspective", Journal of Cardiovascular Magnetic Resonance, vol.8 , pp. 573-580, July 2009, Publisher : Taylor & Francis.

[17]M. R. Ismael, I. Abdel-Qader,"Brain Tumor Classification via Statistical Features and Back-Propagation Neural Network", in IEEE International Conference on Electro/Information Technology (EIT), pp. 252-257, October 2018, Publisher: IEEE

[18] H. H. Sultan, N. M. Salem, and W. Al-Atabany, "Multi-classification of brain tumor images using deep neural network," IEEE Access, vol. 7, pp. 69215–69225, 2019. Publisher: IEEE.

[19] M. Bennaceur, R. Saouli, M. Akil, R. Kachouri, "Fully Automatic Brain Tumor Segmentation using End-to-End Incremental Deep Neural Networks in MRI images" Computer Methods and Programs in Biomedicine, vol 166, pp. 39-49, November 2018, Publisher: ELSEVIER

[20] M. Havaei, A. Davy, D. Warde-Farley, A. Biard, A. Courville, Y. Bengio, C. Pal, P.-M. Jodoin, and H. Larochelle, "Brain tumor segmentation with deep neural networks," Medical image analysis, vol. 35, pp. 18–31, 2017. Publisher: Elsevier.

[21]J. Cheng, W. Huang, S. Cao, R. Yang, W. Yang, Z. Yun, Z. Wang, Q. Feng, "Enhanced Performance of Brain Tumor Classification via Tumor Region Augmentation and Partition", October 2015, Publisher: PLOS ONE

[22]J. Cheng, W. Yang, M. Huang, W. Huang, J. Jiang, Y. Zhou, R. Yang, J. Zhao, Y. Feng, Q. Feng, W. Chen, "Retrieval of Brain Tumors by Adaptive Spatial Pooling and Fisher Vector Representation" June 2016, Publisher: PLOS ONE

[23] M. M. Badža and M. Barjaktarović, "Classification of brain tumors from MRI images using a convolutional neural network," Applied Sciences, vol. 10, no. 6, pp. 1999, 2020. Publisher: Multidisciplinary Digital Publishing Institute.

[24] A. Pashaei, H. Sajedi and N. Jayayeri, "Brain Tumor Classification via Convolutional Neural Network and Extreme Learning Machines" in 8th International Conference on Computer and Knowledge Engineering (ICCKE), pp. 314-319, December 2018, Publisher: IEEE

[25] H. Mohsen, E.-S. A. El-Dahshan, E.-S. M. El-Horbaty, and A.-B. M. Salem, "Classification using deep learning neural networks for brain tumors," Future Computing and Informatics Journal, vol. 3, no. 1, pp. 68–71, 2018. Publisher: Elsevier.

[26] A. Cinar and M. Yildirim, "Detection of tumors on brain MRI images using the hybrid convolutional neural network architecture," Medical hypotheses, vol. 139, p. 109684, 2020. Publisher: Elsevier.

[27] P. Afshar, A. Mohammadi, K. N. Plataniotis, “BRAIN TUMOR TYPE CLASSIFICATION VIA CAPSULE NETWORKS” in 25th IEEE International Conference on Image Processing (ICIP), pp. 3129-3133, September 2018, Publisher: IEEE

[28] P. Afshar, K. N. Plataniotis, “CAPSULE NETWORKS FOR BRAIN TUMOR CLASSIFICATION BASED ON MRI IMAGES AND COARSE TUMOR BOUNDARIES” in IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 1368-1372, April 2019, Publisher: IEEE

[29] H. Siar and M. Teshnehlab, “Diagnosing and classification tumors and MS simultaneous of magnetic resonance images using convolution neural network,” in 2019 7th Iranian Joint Congress on Fuzzy and Intelligent Systems (CFIS), pp. 1–4, IEEE, 2019.

[30] B. Tahir, S. I. M. U G. Khan, T. Saba, Z. M. A. Anjum, T. Mahmood, “Feature enhancement framework for brain tumor segmentation and classification” February 2019, Publisher: Wiley Analytical Science Journals

[31] M. I. Sharif, J. P. Li, M. A. Khan, and M. A. Saleem, “Active deep neural network features selection for segmentation and recognition of brain tumors using MRI images,” Pattern Recognition Letters, vol. 129, pp. 181–189, 2020. Publisher: Elsevier.

[32] Z. N. K. Swati, Q. Zhao, M. Kabir, F. Ali, Z. Ali, S. Ahmed, and J. Lu, “Brain tumor classification for MR images using transfer learning and fine-tuning,” Computerized Medical Imaging and Graphics, vol. 75, pp. 34–46, 2019. Publisher: Elsevier.

[33] M. Sajjad, S. Khan, K. Muhammad, W. Wu, A. Ullah, and S. W. Baik, “Multigrade brain tumor classification using deep CNN with extensive data augmentation,” Journal of computational science, vol. 30, pp. 174–182, 2019. Publisher: Elsevier.

[34] N. Noreen, S. Palaniappan, A. Qayyum, I. Ahmad, M. Imran, and M. Shoaib, “A deep learning model based on concatenation approach for the diagnosis of brain tumor,” IEEE Access, vol. 8, pp. 55135–55144, 2020. Publisher: IEEE.

[35] R. Chelghoum, A. Ikhlef, A. Hameurlaine, and S. Jacquir, “Transfer learning using convolutional neural network architectures for brain tumor classification from MRI images,” in IFIP International Conference on Artificial Intelligence Applications and Innovations, pp. 189–200, Springer, 2020.

[36] M. Togacar, Z. Comert, and B. Ergen, “Classification of brain MRI using hyper column technique with convolutional neural network and feature selection method,” Expert Systems with Applications, vol. 149, p. 113274, 2020. Publisher: Elsevier.

[37] N. Ghassemi, A. Shoeibi, and M. Rouhani, “Deep neural network with generative adversarial networks pre-training for brain tumor classification based on MR 50 images,” Biomedical Signal Processing and Control, vol. 57, p. 101678, 2020. Publisher: Elsevier.

[38] M. Rezaei, K. Harmuth, W. Gierke, T. Kellermeier, M. Fischer, H. Yang, and C. Meinel, "A conditional adversarial network for semantic segmentation of brain tumor," in International MICCAI Brainlesion Workshop, pp. 241–252, Springer, 2017

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