# DETECTION AND CLASSIFICATION OF BRAIN TUMOR USING DEEP LEARNING


**By**

**GHULAM HUSSAIN**

**NATIONAL UNIVERSITY OF MODERN LANGUAGES**

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**GHULAM HUSSAIN**

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# THESIS AND DEFENSE APPROVAL FORM

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**Submitted by:** Ghulam Hussain **Registration #:** 45 MS/SE/S21

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Name of Discipline

Dr. Raheel Zafar
Name of Research Supervisor

Signature of Research Supervisor

Dr. Muzafar Khan
Name of HOD (SE)

Signature of HOD (SE)

Dr. Mohammad Noman Malik
Name of Dean (FE&CS)

Signature of Dean (FE&CS)

August, 2023

# AUTHOR'S DECLARATION

I Ghulam Hussain

Son of Qurban Ali

Registration # 45 MS/SE/S21

Discipline Software Engineering

Candidate of **Master of Science in Software Engineering (MSSE)** at the National University of Modern Languages do hereby declare that the thesis **Detection And Classification Of Brain Tumor Using Deep Learning** submitted by me in partial fulfillment of MSSE degree, is my original work, and has not been submitted or published earlier. I also solemnly declare that it shall not, in the future, be submitted by me for obtaining any other degree from this or any other university or institution. I also understand that if evidence of plagiarism is found in my thesis/dissertation at any stage, even after the award of a degree, the work may be canceled and the degree revoked.

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Ghulam Hussain

Name of Candidate

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# ABSTRACT


**Detection And Classification Of Brain Tumor Using Deep Learning**

A brain tumor is a potentially fatal condition caused by uncontrolled brain cell development that affects human brain cells and the neurological system. Brain tumors are among the leading causes of death worldwide. Therefore, for a patient to receive appropriate medication, a precise and early diagnosis of a brain tumor is essential. It also helps to avoid time-consuming and painful medical procedures. Manual brain tumor identification and treatment takes a long time, is complicated, and contains a human error. As a result, accurate automatic techniques are needed for the segmentation and classification of tumors. Machine learning techniques are employed for early detection and enhanced results. Precise tumor segmentation and classification are important in radio surgical planning and evaluating tumor treatment efficacy. The purpose of this research is to develop a deep learning-based system for segmenting and classifying brain tumors. In this study, a 3D U-Net model is used for the segmentation of MRI images, followed by 3D CNN for the classification of segmented images. BraTs 2019 datasets are used for training and testing the model. This model gets the accuracy of 96%.

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| | | |
|---|---|---|
| **ANN** | **-** | Artificial Neural Network |
| **CT** | - | Computerized tomography |
| **CSF** | - | Cerebrospinal fluid |
| **DSC** | - | Dice score coefficient |
| **fMRI** | **-** | Functional magnetic resonance Imaging |
| **HGG** | **-** | High-grade glioma |
| **LGG** | | Low-grade glioma |
| **MRI** | | Magnetic resonance imaging |
| **MRS** | | Magnetic resonance spectroscopy |
| **PET** | | Position emission tomography |
| **RNN** | | Recurrent neural network |
| **ReLU** | | Rectified linear unit |
| **SPECT** | | Simple photon emission computed tomography |
| **SVM** | | Support vector machine |
| **WHO** | | World health organization |

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# CHAPTER 1

# INTRODUCTION

## 1.1 Overview

Brain cancer is an irregular development of brain cells, some of which are benign and some of which are malignant. Tumors can develop directly from the tissue of the cerebrum or they can spread from another area of the body. Treatment effectiveness varies according to the category, size, and position of the tumor. A situation in which tumor cells originate in the brain's tissues or in which a tumor initially develops in another part of the body before spreading to the brain (National Cancer Institute, 2020). The brain is essential to humans because it regulates several bodily processes. Thus, when a brain tumor develops, significant symptoms might appear that could have an impact on the health and quality of life of the patient [1].

Malignant and benign tumors are the two categories under which most brain tumors fall (National Cancer Institute, 2020). The first category of tumors that begin in the brain and secondary that have spread outside the brain are two categories of cancerous tumors that can be distinguished. Because most people don't comprehend brain tumors, many patients have lost their lives because they didn't get an early diagnosis and treatment in time [2].

## 1.2 Medical Imaging of the Brain

Early detection of brain tumors provides precise treatment opportunities. Medical imaging is essential in detecting some early identifying tumor symptoms by examining various types of images such as X-rays, CT scans, MRIs, etc. There are several diagnostic methods available to examine pathological illnesses using digital imaging and blood tests on humans. Image segmentation is one of them, and it's crucial for making a precise diagnosis, keeping track of diseases, and providing treatments [3, 4].

A brain tumor is highly hazardous to human health that usually occurs due to uncontrolled growth of brain tissue. Many researchers have worked to find ways to better interact with medication for effective treatment, but using imaging techniques gives neurologists the right information to find the right position. These days, excellent medical imaging techniques, including MRI images, improve the effectiveness of computer-aided brain tumor identification [4].

### 1.2.1 Brain Structure

The brain stem, cerebellum, and cerebrum are the three parts of the brain. The greatest portion of our brains is called the cerebrum. There are two hemispheres in it. The occipital lobe, parietal lobe, temporal lobe, and frontal lobe are the four lobes that make up each hemisphere. Cortex refers to the cerebrum's outside. Gray matter, which includes the cortex, is made up of nerve cell bodies. Long nerve fibers, often known as white matter, connect various parts of the brain underneath the cortex. Deep in the cerebrum is a structure called basal ganglia or basal nuclei, which consists of caudate, putamen, and globus pallidus. The cerebrum controls the activity of thoughts, moments, and sensation feelings [5].

The second largest part of the brain is the cerebellum. It is located on the backside of the head and connected to the brain stem. It controls the movement, posture, and balance of our bodies [5]. The spinal cord is attached to the brain stem, which is located at the base of the brain. And consist of the midbrain, pons, and medulla oblongata.

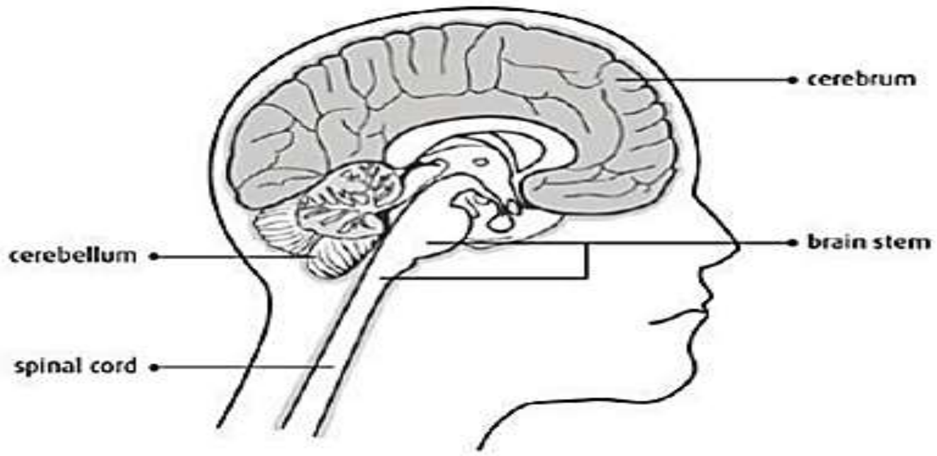


**Figure 1. 1:** Basis Structure of the human brain [5].

The brain stem controls many autonomic functions such as respiration, heartbeat, body temperature, sleeping cycle, digestion, sneezing, and swallowing. The whole brain is covered by three layers called meninges (Dara, pia, and arachnoid) matter.

And there is a fluid in between these layers called cerebrospinal fluid(CSF) which act as a cushion from injury to brain tissues [5].

## 1.3 Brain Anomalies

When the human body undergoes a disease that has a significant impact on one's quality of life. Brain cancer is also a deadly disease that affects the human brain. According to the study, a brain tumor is caused when normal brain cells get some effect by the DNA. These abnormal cells prevent healthy cells from dying and replicating more quickly. As a result, tumors will occur, when these abnormal cells grow in size. Abnormal growth of tissues causes increased internal head pressure and also causes brain enlargement or cerebrospinal fluid blockage. A loss of connection between neurons and the interconnected morphology of the brain results from any breakdown of brain tissues. These result in dementia, a condition that can be quite serious. Another side effect of dementia is neuronal loss. It is characterized by a continuous decline in memory and fundamental brain function, which is severe enough to limit social and occupational abilities. Alzheimer’s disease causes memory loss. The patient's brain state changes from normal to abnormal as a result, maybe completely erasing their capacity for learning and their ability to see the world visually. Therefore, prior treatment is needed to sustain the quality of life. Together with computer scientists, neurologists are developing the quickest computerized approach for processing brain scans to accurately identify brain damage [5, 6].

### 1.3.1 Causes and Classifications

#### I. Causes

The cause of brain tumors is not completely understood, just like with other diseases. Other than an infection to ionizing radiation, there is currently no clear evidence linking environmental causes to brain tumors. A few components that are assumed to be associated with the development of brain tumors include viral infections, carcinogens, radiation, genetics, and embryonic remains; nevertheless, each theory is only relevant for revealing the origin of particular types of tumors [7, 8]. Numerous experts have connected smoking to cancer, but the precise pathogenic reasons are still unknown. There is currently insufficient data to indicate definitively that some linked factors and human brain tumors are connected. Multidisciplinary collaborative research is still needed to provide a thorough explanation of the origin of brain tumors. Headaches, convulsions, eyesight issues, vomiting, and mental abnormalities are among the symptoms [9].

## II. Classification

For their treatment, brain tumors must be categorized. The classification of the brain tumor can be established, and the appropriate treatment plan can then be provided, to produce the best possible treatment results.

Tumors are a representation of the body's cells growing out of control in any section of the body. However, a tumor in the brain is an uncontrolled development of either benign or malignant brain cells. Malignant (heterogeneous) tumors contain active (cell) cells while benign brain tumors do not and share structural similarities with them. Gliomas and Meningiomas are examples of low-grade cancers that are considered to be benign tumors, whereas astrocytomas and glioblastomas are examples of high-grade cancers that are categorized as malignant tumors [10].

The brain is essential to humans because it regulates several bodily processes. As a result, as a brain tumor grows, it may cause noticeable symptoms that could affect the patient's health and quality of life. The World Health Organization (WHO) classified brain tumors into four classes (I, II, III, and IV) in 2016 based on molecular characteristics and histopathology. A tumor's grade determines how dangerous it is. Patients with grade I/II low-grade gliomas (LGG) can live. High-grade gliomas (HGG) grade III/IV put patients in danger and significantly reduce their chances of survival. If LGG is not identified and treated right away, it could develop into HGG [11].

The most dangerous form of tumor and the most serious glioma is glioblastoma. Glioblastoma is distinct from other types of tumors in this class because it produces necrosis (dead tissue) and abnormally quick blood vessel growth.

The most severe form of glioma and the most dangerous variety of astrocytoma is glioblastoma. Due to the irregularly quick growth of the development of necrosis (dead cells) and blood vessels over the majority of the tumor, glioblastoma is distinct from all other types of the tumor class. The two primary categories of brain tumors are Primary and secondary brain tumors (malignant tumors). Gliomas are a type of brain tumor in which one type of cell grows slowly in the brain. It is produced by astrocytes, which are non-neuronal brain cells. Primarily, primary tumors are less dangerous, but they put a lot of stress on the brain, which causes it to malfunction. The secondary tumors are more aggressive and spread into adjacent tissues more quickly. Secondary brain cancers have their origins elsewhere in the body. This kind of tumor is caused by a cancer cell that spreads throughout the body, including the brain, lungs, and other organs. The subsequent brain tumor is highly aggressive. Lung cancer, kidney cancer, bladder cancer, etc. are the leading causes of secondary brain tumors [12].

## 1.4 Treatment and its risk

That’s why early tumor diagnosis and accurate categorization are crucial for successful treatment. Treatment for brain tumors typically involves a combination of surgery, radiotherapy, and chemotherapy. The specific treatment approach will depend on the nature, location, and size of the tumor, as well as the patient's age and overall health [13, 14].

Surgery, Chemotherapy, and Radiotherapy are the commonly used treatment procedures.

### 1.4.1 Surgery

Surgery is often the first line of treatment for brain tumors. The purpose of surgery is to eliminate as much of the tumor as possible while preserving brain function. The type of surgery performed will depend depending on the patient's general health, the location and size of the tumor, and other factors.

### 1.4.2 Radiotherapy

To destroy cancer cells or reduce tumors, radiotherapy employs high-energy X-rays or other forms of radiation. Radiotherapy can be administered externally (using a machine to deliver the radiation to the brain) or internally (using radioactive implants placed inside the brain).

### 1.4.3 Chemotherapy

Drugs are used in chemotherapy to either kill or inhibit the growth of cancer cells. Several medical imaging tools, including X-ray, ultrasound, computerized tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), computerized tomography (CT), and simple photon emission computed tomography (SPECT) scans, are used to detect brain cancer [13, 14].

## 1.5 Brain tumor identification procedures

Testing of your physical condition and a review of your medication history are the first steps in the identification and localization of a brain tumor. Brain biopsy testing and computerized procedures are the two physical examination techniques available for identifying brain tumors.

### 1.5.1 Biopsy Test of Brain

To identify brain disorders, this test is used. For microscopic examination, a little portion of brain tissue is separate from brain cells, which is used for the testing of tumors. Based on the medical history of patients, three additional tests may be recommended which are Brain Open biopsy, Stereotactic biopsy, and Needle biopsy. In a **needle biopsy brain test**, a tiny hole is drilled in the brain's skull to segment a small section of brain tissue, and a narrow, hollow needle is then inserted for examination.

For the least painful and most accurate way to observe brain tumors, the stereotactical biopsy is used. In Stereotactic biopsy, data are collected from 3D imaging scanning technologies such as CT and MRI.

Open brain biopsy is a common type of brain surgery. In this approach, a small portion of the brain cells is removed from the brain which uses the brain tumor examination. and surgically treated during this treatment. It is a riskier process that requires more recovery time [15].

### 1.5.2 Computer-Based Brain Imaging Test

Brain imaging techniques fall into two groups: structural imaging techniques and functional imaging techniques. Structural imaging techniques can show each component of the brain's tissue. X-rays, MRI, CT, and ultrasound are the most used brain imaging techniques.

#### I. X-ray imaging

One of the earliest methods for examining the bones in the human body was X-ray imaging. It is a transmission-based method for creating 2D pictures of exposed tissue using ionizing radiation. It consists of X-ray beams that are absorbed by various densities of materials. It contains X-ray beams that are absorbed by various densities of materials. X-rays are frequently quick and easy techniques. However, it is unable to see tumors that are hidden behind the skull or spinal bones. Therefore, X-rays are not commonly used for brain tumor detection [16].

## II. Computerized Tomography (CT)

Computerized Tomography (CT) a chain of X-rays are taken from various angles. It is used to examine the body's interior organs and offers details on the soft tissue and blood vessels found there. Compared to X-rays, CT is a more modern technique that can identify more details about bone fractures, brain abnormalities, and the position of tumors. The computerized CT produces combines two-dimensional images of interior organs them to produce 3D images for a better view and to get more details. Many medical professionals advise using computed tomography imaging when there is bleeding, a blood clot, or a malignancy. But CT raises the risk of cancer because it uses stronger X-rays which emit ionizing radiation that can potentially damage live tissue. Fig 1 shows some images of the CT scan [17].

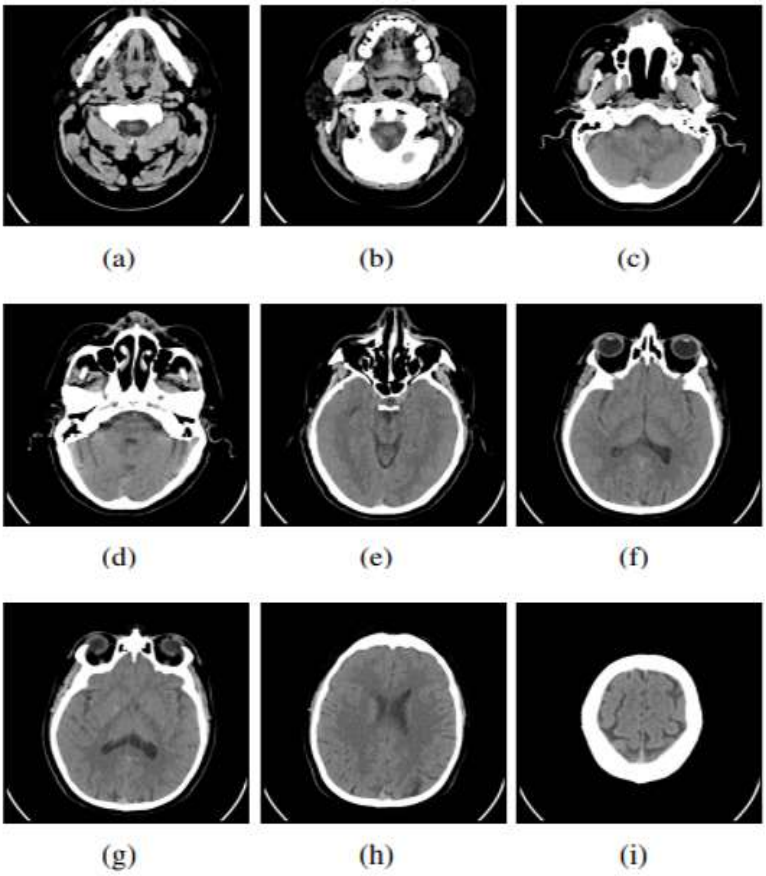


**Figure 1. 2:** CT scan images [18]

## III. Magnetic Resonance Imaging (MRI)

Magnetic Resonance Imaging (MRI) is an effective method for analyzing medical images of the brain and body structure. It is particularly useful for detecting brain tumors due to its high-contrast images that provide detailed information about the brain's soft tissue. MRI utilizes three planes (axial, sagittal, and coronal) to give a comprehensive view of the brain, spinal cord, and blood vessels. Unlike other techniques, it does not use ionizing radiation and instead uses a combination of magnetic fields and radio waves to produce clear 2D or 3D images. One benefit of MRI is that it uses no radiation, making it a safer procedure than CT [6, 17].It is important to understand the basics of how MRI works before discussing its characteristics. MRI is used to determine the size of tumors. To enhance the image, a special dye called a contrast medium is given to the patient before the scan, either through injection, pill, or liquid. The type of scan performed, whether it be of the brain, spinal cord, or both, depends on the type of tumor detected. There are different types of MRI, and the appropriate one to use is determined by the neurologist based on their examination.

1: Intravenous (IV) gadolinium-enhanced MRI. The most common way to get a clearer image of a brain tumor is by using an intravenous (IV) enhanced MRI with a contrast agent called gadolinium. This involves getting a standard MRI first, followed by an IV infusion of the contrast agent. Then, another MRI is done to capture additional images with the dye.

*2:* Diffusion-weighted imaging. Diffusion-weighted imaging, an MRI method, helps to show the cellular structure of the brain.

*3:* Perfusion imaging. Perfusion imaging, a different method, is used to determine how much blood is getting to the tumor. The effectiveness of treatment could be predicted by doctors using these methods.

*4:* A spinal MRI may be used used to identify tumors in or around the spinal area.

*5:* A functional MRI (fMRI). It gives details about the position of particular brain regions that control speech and muscle movement. The patient is required to perform specific tasks during the fMRI test, which result in changes in the brain that may be seen on the fMRI image. This test aids in surgical planning so that the surgeon can remove the tumor without harming the brain's functioning areas.

*6: Magnetic resonance spectroscopy (MRS).* Using an MRI, a test called magnetic resonance spectroscopy (MRS) can give details about the material composition of the brain. It can serve in distinguishing between newly formed tumor cells in the brain and any dead tissue produced by prior radiation treatments.[https://www.cancer.net/].

### i. Working of MRI

During an MRI scan, a powerful magnetic field is passed through the patient. The areas of low energy (parallel) and high energy (anti-parallel) in the magnetosphere are caused by this magnetic field, causing the body's photons to adapt. Then the radio frequency is utilized. Characteristics of MRI images. The following factors make the MRI particularly helpful for studying soft tissues and the neurological system.

1. CT, SPECT, and PET use ionizing radiation, however, MRI does not use high frequencies or ionizing radiation, which are both hazardous to human health.

2. Compared to other imaging technologies, MRI delivers images with great contrast.

3. Both 2D and 3D images can be produced by an MRI, but 3D scans in particular provide a greater level of information for locating diseased brain tissue [6].

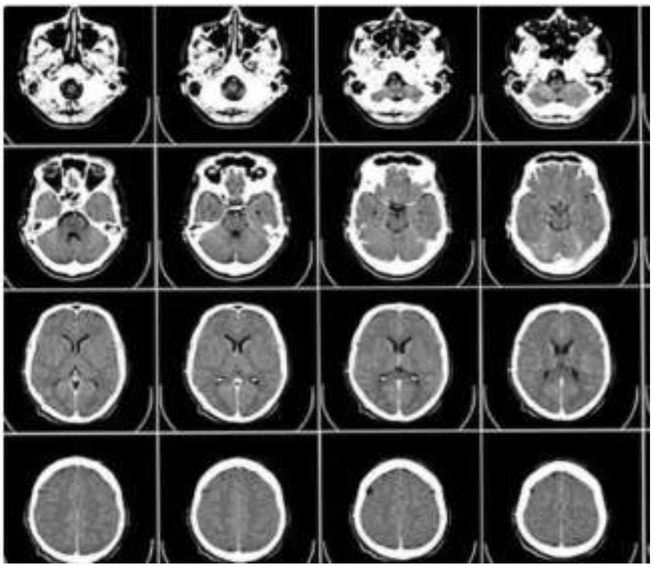

**Figure 1. 3:** MRI images [18]

## 1.6 Motivation

A brain tumor is described as the irregular development of cells inside the brain or central spinal canal. Some tumors may be malignant, therefore it's important to find them early and treat them. People may have brain tumors without ever knowing it. Being aware of the danger because the precise origin and exact set of symptoms are not known. Primary brain tumors may be benign or malignant.

When cells are dividing and developing abnormally, it causes brain tumors. When a tumor is diagnosed using diagnostic imaging techniques, it seems to be a solid mass. Brain tumors come in two different varieties: primary brain tumors and metastatic brain tumors. Primary brain tumors are those that develop in the brain and do not spread while metastatic brain tumors are those that develop in other parts of the body and spread all across the brain.

The location, size, and kind of tumor all affect the symptoms of a brain tumor. It happens when the tumor exerts pressure on the cells in its vicinity. Additionally, it happens when the tumor blocks the movement of fluid throughout the brain. Headache, nausea, and vomiting, as well as balance and walking issues, are common symptoms of brain tumors. Diagnostic imaging techniques like CT scans and MRIs are used for tumor detection. Both techniques are used for brain tumor detection which is depending on the position of the tumor and the inspection goal. MRIs are mostly used because they are easy to analyse and provide precise information.

The primary goal of brain tumor detection is to identify different forms of tumors, in addition, to classifying tumors also. It can therefore be helpful in situations when there is a need to ensure that a tumor is positive or negative. It can detect tumors from images and report whether they are positive or negative.

## 1.7 Problem Statement

Accurate detection and classification of tumor (using MRI) is challenging as it may vary in size and location [9]. Although traditional 2D methods have been utilized, they often struggle to effectively address these challenges [19]. Since, the MRI are inherently 3D images [20] hence, it is crucial to use a 3D based system (U-Net and CNN) for segmentation and classification of tumors.

## 1.8 Research Questions

**RQ1:** How to segment brain tumor accurately using 3D U-Net model ?

**RQ2:** How to improve the classification of tumor using 3D CNN ?

## 1.9 Research Objectives

- To segment brain tumor accurately using 3D U-Net model.
- To improve the classification of tumor using 3D CNN.

## 1.10 Scope of Study

There is a wide range of research work performed on the accurate identification and classification of tumors using different techniques. The scope of this research is to explore the combination of a 3D-Net model for segmentation and a 3D Convolutional Neural Network (CNN) for classification in the field of medical imaging, with the objective of increasing the accuracy of segmentation and classification tasks. By leveraging the spatial information present in 3D medical volumes, the proposed approach aims to achieve more accurate segmentation, followed by accurate classification of the segmented images. The research focuses on investigating the effectiveness of the 3D-Net model for accurate segmentation. Additionally, the scope also includes evaluating a 3D CNN for classification of the segmented images, with the aim of improving the accuracy of the classification results.

## 1.11 Contribution and Significance

A major challenge is the detection and classification of infectious tumor areas from MRI images**.** Manual detection and classification of tumors are complex, time-consuming, and have a lot of chance of error. Manual detection depends upon the radiologist's experience and there are more chances of human errors**.** If an automated system is designed that can detect and classify the tumors automatically without human intervention with high accuracy [21]. It will be a big contribution to the medical field. Numerous efforts have been made in the early detection and classification of brain tumors using an automated system. In this research work, a framework is proposed through which tumors will be detected and classified with higher accuracy. The proposed system will be able to distinguish between the various types of brain tumors with great accuracy.

## 1.12 Thesis Structure

Chapter 1 gives a brief introduction to the brain structure, brain abnormalities, brain tumor cause, and classification. Systems used for brain tumor detection and treatment purpose will also be explained. I will briefly outline the objective, purpose, and significance of our thesis.

Chapter 2 contains literature reviews that provide a summary of individual papers.

Chapter 3 provides an overview and background knowledge of existing techniques used for brain tumor segmentation and classification using 3D U-Net and 3D CNN models.

Chapter 4 presents details of datasets, implementation and its results, tools, and technology used to achieve the required results.

Chapter 5 contains conclusions about brain tumor segmentation and classification using deep learning.

## 1.13 Summary

This chapter provides a brief overview of brain tumors and its subtype. The various types of brain tumors, their characteristics, and their causes of the brain have been covered. Different types of techniques and tools used for the detection and treatment of brain tumors, especially MRI, are briefly discussed. I briefly outlined the purpose of the work and the goal of accomplishing it. Finally, I provided a brief description of the thesis contribution and its structure.

# CHAPTER 2

# LITERATURE REVIEW

## 2.1 Overview

For accurate segmentation and classification of brain tumors, several research has been done.Many researchers used different techniques for segmentation and classification purpose. In this literature review focused on those articles that used deep learning techniques for brain tumor segmentation and classification purpose. Some works obtained a significant outcome utilizing various methodologies, whilst others did not.

## 2.2 Existing Literature

In recent studies, automatic segmentation and classification using of brain tumors using DL-based structures have been explored extensively.

In [22] create a system for automatically segmenting brain tumors. The process includes the subsequent steps. To detect local dependencies, a multi-cascaded convolutional neural network (MCCANN) was initially used. Conditional random fields (CRFs) were employed in the following stage to extract Information related to the location or position and filter out certain false positives for effective segmentation. At the final stage, the brain tumor was located using three segmentation frameworks, including the axial, coronal, and sagittal perspectives. The accuracy of the model was 74%.

In [23] used a watershed segmentation technique along with a KNN to identify brain tumors. This method produces more accurate tumor segmentation findings, however, it is unable to accurately segment complex images that contain the tumor area. For tumor segmentation, FR-MRINet.Accuracy of the model was 86%.

In [24], a 33-layer deep network comprising an encoder and a fully linked decoder, was used. To carry out the tumor's pixel-by-pixel segmentation suggest an encoder-decoder approach. The dice score of the model was 0.73.

In [25] ,for segmenting brain tumors, many segmentation methods have been suggested. The two biggest barriers to segmenting brain tumors are noise and intensity heterogeneity. For removing noise and other artifacts, they used discrete wallet transformation(DWT) and discrete cosine transformation(DCT). To increase the performance and reduce the complexity, for brain tumor segmentation the author used a 2D-Unet model, and for classification purposes, SVM classifiers were used. Additionally, they also compared the classification accuracy of different classifiers. Comparison is based in two ways. BraTs 2019 dataset was used to verify the methodology. 2D U-ConvNet is used for segmentation. One way is with features extraction and another is without features extract. They got an accuracy of 93% for the segmentation of tumors.

In [26], to improve medical imaging's precision and reduce its degree of ambiguity, the author proposed a 3D convolutional deep learning architecture. They trained their model with four channels of MRI images which were FLAIR contrasts,contrast-enhanced, T2w, T1w, and non-enhanced MRI images. Publicly accessible data sets: OASIS, IBSR, and LPBA40 were used for training.

In [27] for accurate tumor classification, the author used a model which was a combination of CNN and multiclass SVM. Instead of CNNs with softmax, convolutional neural networks (CNN) with SVM were employed. CNN-SVM achieved a substantially better outcome than CNN with Softmax. The Figshare open dataset's three different MRI scan types were used. The datasets were used to train CNN to extract features. The CNN function was coupled with Multiclass SVM to enhance performance and precision.The overall accuracy of the model was 89 %.

In [28], different transfer-based deep learning techniques with different classifiers were used for the accurate identification and classification of brain tumors. They combined different CNN techniques with different classifiers. Transfer learning techniques was DenseNet201, InceptionV3 , ResNet50, InceptionResNetV2, , VGG-19, Xception, and VGG-16.For accurate classification of a different tumor, they used five classifiers Gradient Boosting, Random Forest, Support Vector Machine, Ada Boost, and Decision Tree. The performance metrics such as Cohen’s kappa, F1-score, recall, precision, accuracy, AUC, Jaccard, and Specificity, were performed through which the feature extraction and classification performance of the above techniques were measured. VGG-19 and SVM techniques show very high accuracy as compared to other techniques. 2D MRI images were used for brain tumor detection The classification accuracy of the proposed model was 92%.

In [29] CNN U-Net 2D was used for the segmentation of brain tumors. For segmentation of the brain tumor, skip connection, dropout, and convolutional transpose are used with CNN U-Net 2D. BRATS2018 and BRATS2020 datasets were used for training and testing purposes. The model accuracy was 90%.

In [30] CNN was used for brain tumor classification into three classes namely pituitary, meningioma, and glioma. Before applying CNN, they preprocessed the datasets by using a Gaussian filter to filter images, and after that histogram equalization technique was applied to the filtered images. Then CNN models were trained to classify the tumor. The accuracy of the result was 92.39%. In [31] U-net with VGG-16 was used for semantic segmentation of brain tumors. They modified the VGG16 by adding an expensive layer at the end of the VGG16 which consists of several up-sampling layers and convolution layers to make it resemble U-net architecture. With transfer learning, the UNet-VGG16 model was used for training MRI images. This method had a high accuracy of about 96.1%. The higher correct classification ratio of the proposed model was 95.69%. But the model required a large number of datasets.

In [32] the author proposed two different techniques for the detection and classification of brain tumors. For brain tumor detection, they used U-net architecture with ResT Net 50 as a backbone. Other deep learning techniques such as Dense Net 201, InspectionV3, ResT-Net 50, and Mobile Net V2 were also used for tumor detection. For tumor classification they used NASNet. For increasing accuracy, they applied data augmentation techniques.

The ResTNet50 U-net segmentation architecture comprises an encoder and decoder. At the end of ResTNet50, the encoder was applied by removing the pooling and fully connected layer. The decoder consists of five blocks, each containing 2 × 2 up-sampling layers bounded by convolution layers, Relu, and batch normalization layer. They achieved a 0.9504 score. The proposed techniques showed better accuracy but the techniques required a large number of datasets for training and testing, which caused increased computational complexity.

In [33] for the automatic segmentation of Glioma tumors, an improved U-Net-based architecture was proposed. For the separation of block slices of MRI images, firstly two-step preprocessing techniques were used. After that, the proposed model was used to segment the brain tumor from MRI images. Two-pathway-residual (TPR) blocks were added to the UNet architecture. Accuracy, Dice, sensitivity, Specificity, and PPV were used for the Evaluation of the model. TRP blocks explore both local and global features. Using this technique, sensitivity and DSC were improved. DSC and sensitivity of the proposed model were 89.76%, and 89.19% respectively.

In [34] the author proposed new techniques for brain tumor segmentation using 3D volumetric MRI images. For using, 3D volumetric MRI images they proposed U-Net with separable 3D convolutions. They divided each 3D convolution into three branches namely, coronal, sagittal, and axial. Brats 2018 datasets were used for testing of proposed techniques. The average Dise score is 0.8694 and 0.78347 for segments of the enhanced tumor and the whole tumor.

In [35] proposed a new model named a patch-wise U-net architecture. In the proposed methodology, before training the model, the MRI images are divided into non-overlapping patches. After that, they train the network which identifies the distinct input patches and provides predictions. The Dice similarity coefficient (DSC) score of the proposed was 0.93. The datasets used for training were accessed from two open sources Internet Brain Segmentation Repository (IBSR) and Open Access Series of Imaging Studies (OASIS). Data augmentation techniques were also used. This model shows better results but it also required a large number of labeled datasets.

In [36] the author proposed a technique named as LU-Net deep learning techniques. The datasets contain 253 images.155 images were classified as tumor images, while 98 MR images are classified as normal images. Data augmentation techniques were implemented to increase the number of datasets. After that, the VGG-16 and LU-Net deep CNN model was trained. The suggested strategy performs better than previous deep neural models at segmenting and categorizing MR images for the identification of brain tumors. Precision, Recall, Specificity, F-score, and Accuracy were five separate statistical assessment measures used to analyze the performance of the suggested model.

In [37] for early detection and classification of brain tumors, the author proposed a transfer learning approach using CNN. Five different deep-learning techniques were trained for the early detection and classification of different type of brain tumor which was VGG16, MobileNetV2, EfficientNetB0, Xception, and ResNet50.In the preprocessing of images, for noise removal, Gaussian blur filter, BM3D denoised, and Total Variation smoothing were applied. Data augmentation techniques were also applied to increase the datasets. The proposed model got good accuracy but they train the datasets with five different CNN models using transfer learning techniques which causes to increase processing timing.

In [38] the author proposed a model to use 3D images instead of using 2D images. The model name was self-excited compressed dilated convolution (SECDC) which was based on the 3D-U Net model and proposed an improved 3D model. In the SECDC model, reduced the convolution by $1 \times 1 \times 1$, and the 3D squeeze-and-excitation (3D-SE) module was trained for automatic learning of each layer. Dice coefficient, Sensitivity, PPV index, and Hausdorff index parameters were used for calculating the performance of the suggested model. Brats 2019 datasets were used for training. The overall Dice coefficient of the proposed model for the overall tumor was 0.87, for the tumor core was reach 0.84, and for the enhanced tumor was 0.80. For practical purposes, it is very difficult to train large label datasets and the computation time was very long.

In [39] the author proposed a new model by using 3D MRI images. For brain tumor segmentation, deep learning techniques achieve better results but, deep learning techniques require a large number of memory and other resources. To resolve the memory issues, they proposed a novel technique named as Memory-Efficient Cascade 3D U-Net (MECU-Net) for brain tumor segmentation. The technique consists of MECU-Net, multi-scale feature fusion module (MSFFM),up-sampling, cascade strategy, and multi-loss module. In MECU-Net techniques, decrease the number of downsampling channels to overcome memory issues. After that, they applied Multi-Scale Feature Fusion Module(MSFFM), cascade strategy and by combining the weighted loss and edge loss, they achieve high accuracy with less memory requirement. BraTS 2019 datasets were used for training and testing purposes. They achieved the average Dice coefficient of the model which was 0.824 for the tumor core.

In [40] the author proposed techniques for segmentation and classification. An effective framework for brain tumor segmentation and classification using deep learning techniques was used. They used 3D-Unet and CNN for tumor segmentation and classification. They used different datasets for segmentation and classification. For segmentation purposes, they utilized the Brats 2020 datasets while for classification purposes they used the Kaggle dataset. They classify the tumor into four categories such as no-tumor, pituitary, meningioma, and glioma. The overall accuracy of the framework was 90%.

In [41] the author proposed new techniques to remove different noise. Noise, such as Gaussian noise, salt & pepper noise, and speckle noise, may be detected during the acquisition of an MRI scan. The effectiveness of classification may suffer. Therefore the author proposed a new noise-removing technique named modified iterative grouping median filter. For segmentation purposes, the author used VGG16 deep learning techniques. The model 3.83% enhancement in accuracy.

In [42] the author used deep learning techniques for brain tumor segmentation and classification. Segmentation was performed by using the U-Net model and for classification purposes, they used different CNN models such as VGG16, Resnet50, Inception V3, and SqueezeNet.Segmentation Dice score was 78% U-Net architecture and classification accuracy was 87% using resnet 50, 82% using SqueezeNet, 80% using vgg16, and 72% using Inception v3.

In [43], the author used a context-aware deep learning technique to segment, classify, and predict overall survival in brain tumors. For brain tumor segmentation, the author used 3D context-aware deep learning. After segmentation,3D CNN was used for the classification of the tumor segments to determine the tumor subtype. The uses of a conventional machine learning technique to accomplish overall survival prediction by extracting characteristics. For extracting features, gray-level co-occurrence matrix(GLCM) and intensity were implemented. For feature selection, LASSO was applied and the end linear regression was used for survival prediction. The Multimodal Brain Tumor Segmentation Challenge 2019 (BraTS 2019) dataset was utilized for tumor segmentation, while the Computational Precision Medicine Radiology-Pathology (CPMRadPath) Challenge on Brain Tumor Classification 2019 dataset was used for classification and overall survival prediction. Dice score coefficient(DSC), Hausdorf distance at percentile 95 (HD95), for classification accuracy, and mean square error were used for performance evaluation. The DCS of the suggested model was 0.821 for segmentation and DCS for classification was 0.693 and the overall survival prediction accuracy was 0.484 for the testing phase.

**Table 2. 1:** Existing Studies on brain tumor segmentation and classification

| Year | References | Methods | Accuracy |
|---|---|---|---|
| 2019 | [22] | Multi-cascaded convolutional neural network (MCCANN) for accurate segmentation of tumor. | The model accuracy was 74% |
| 2018 | [23] | Using a watershed segmentation method and the KNN to detect brain tumors. | The accuracy of the model was 86% |
| 2022 | [24] | The tumor cells were identified using an 33 layer of encoder-decoder-based technique. | The dice score of the model was 0.73 |
| 2022 | [25] | 2D-Unit model for brain tumor segmentation and classification purposes SVM classifiers were used. | Segmentation accuracy was 93% and Classification Accuracy was 91% |
| 2021 | [26] | For brain tumor Classification the author used CNN with SVM rather than CNNs with softmax. | Have a very good accuracy for Classification |
| 2021 | [27] | CNN with SVM for Classification of tumor. | Accuracy of classification was 89% |
| 2022 | | VGG-19 and SVM | Classification accuracy was 92% |

| | | | |
|---|---|---|---|
| 2022 | [29] | CNN U-Net 2D was used for the segmentation of brain tumors. | The overall accuracy of segmentation was 90% |
| 2021 | [30] | CNN was used for brain tumor classification into three classes namely glioma, meningioma, and pituitary. | The accuracy of the model was 93% |
| 2020 | [31] | U-net with VGG-16 was used for semantic segmentation of brain tumors. | This method had a high accuracy of about 96.1% |
| 2021 | [32] | For brain tumor detection, they used U-net architecture with ResT Net 50 as a backbone. For tumor classification they used NASA. | Show higher accuracy for segmentation and classification. Overall 0.95 |
| 2021 | [33] | For the automatic segmentation of Glioma tumors, an improved U-Net-based architecture was proposed. | DSC and sensitivity of the proposed model were 89.76%, and 89.19% respectively. |
| 2019 | [34] | For segmentation of 3D volumetric MRI images, they proposed U-Net with separable 3D convolutions. | The average Dise score is 0.8694 and 0.78347 |
| 2019 | [35] | The segmentation of brain tumors was accomplished using patch-wise U-net architecture. | Dice Similarity Coefficient (DSC) score was 0.93. |
| 2022 | [36] | The author proposed a technique named as LU-Net deep learning | The overall accuracy of the model was 90% |

| | | | |
|---|---|---|---|
| | | techniques. After that, the LU-Net and VGG-16 deep CNN model was trained | |
| 2021 | [37] | Five different deep learning techniques were trained for the early detection and classification of different type of brain tumor which was VGG16, MobileNetV2, EfficientNetB0, Xception, and ResNet50 | The overall accuracy of the model was 92% |
| 2022 | [38] | They proposed a new model named self-excited compressed dilated convolution (SECDC) which was based on the 3D-U Net mode | The dice coefficient of the proposed model for the overall tumor was 0.84 |
| 2022 | [39] | To resolve the memory issues, they proposed a novel technique named Memory-Efficient Cascade 3D U-Net (MECU-Net) was used | The dice coefficient of the model was 0.824 for the tumor core. |
| 2021 | [40] | For brain tumor segmentation, the 3D U-net model was used, and the CNN model for the classification | The overall accuracy of the framework was 90%. |
| 2022 | [41] | Noise, such as speckle noise, salt & pepper noise, and Gaussian noise, may be detected during the acquisition of an MRI scan. The author proposed a new noise- | 3.83% enhancement in accuracy. |

| | | | |
|---|---|---|---|
| | | removing technique named modified iterative grouping median filter | |
| 2020 | [42] | Segmentation was performed by using the U-Net model and for classification purposes, they used different CNN models such as VGG16, Resnet50, Inception V3, and SqueezeNet for segmentation | 78% U-Net architecture and classification accuracy was 87% using resnet50, 82% using SqueezeNet, 80% using vgg16, and 72% using Inception v3 |
| 2020 | [43] | For brain tumor segmentation, the author used 3D context-aware deep learning. After segmentation,3D CNN was used for the classification of the tumor segments to determine the tumor subtype. The uses of a conventional machine learning technique to accomplish overall survival prediction by extracting characteristics. The Multimodal Brain Tumor Segmentation Challenge 2019 (BraTS 2019) dataset was utilised for tumour segmentation, while the Computational Precision Medicine Radiology-Pathology (CPMRadPath) Challenge on Brain Tumor Classification 2019 dataset was used for classification and overall survival prediction. | The DCSof the suggested model was 0.821 for segmentation and DCS for classification was 0.693 and the overall survival prediction accuracy was 0.484 for the testing phase. |

## 2.3 Mri Image Analysis: Techniques For Segmentation And Classification

### 2.3.1 Overview

Image processing is a technique used to extract some useful information from images by performing some operation on them. It is also defined as analyzing the images by using computerized algorithms according to the application. Mathematical representation of the image and performing some process to obtain useful and required information by improving its characteristics or by modifying its features. In digital image processing, digital images are processed through an algorithm using a digital computer. Through the digital image process, a wide range of algorithms can be applied to an image to get the required information.

### 2.3.2 Digital image Representation

In general, digital images are represented in two-dimensional matrices. Suppose two independent variables x and y of function A. The function A(x,y) represents the image and can be referred to as the intensity or impulse function. The variables x and y represent the row and column of the pixels in the image, respectively. In this notation, A(x, y) is the intensity of light for the pixel located at row x and column y in the image. Intensity representation is the most commonly used method for representing digital images on a computer [44]. Based on this notation, any digital image can be represented in the form of a matrix as follows:

$$A(x,y) = [A(1,1), A(1,2), \ldots (1,x) \quad A(1,1), A(1,2), \ldots (1,x)] \qquad 1$$

### 2.3.3 RGB Image

Compared to computerized systems, the human visual system is more diverse and unique. Humans are better at deriving information from images and obtaining details from colors than digital machines. Three different wave types, which correlate to the colors Red, Green, and Blue, can be detected by these human brains. By combining the intensity of these three primary colors, the brain then creates all the other colors. In RGB images, each pixel's color is created by combining the three colors' intensities. An RGB (red, green, blue) image of an MRI (magnetic resonance imaging) scan is a digital representation of the scan that uses the three primary colors of light to create a full-color image. The image is created by combining the individual grayscale images of the MRI scan taken at different wavelengths of light. Every pixel in the image is assigned a particular combination of red, green, and blue intensities, which are used to create the final full-color image.

### 2.3.4. Image Segmentation

During analyzing and processing of images, the most important specification for image processing systems is to locate the region of interest. These locations can be identified using some distinct characteristics. There is a wide range of approaches that enable computers to find out the region of interest. Different techniques and algorithms are used to differentiate normal and abnormal forms of medical images. The region is named as Region of Interest (RIO). Image segmentation is the technique that divides an image into small sections based on a specific feature. In digital image processing, different segmentation techniques are used to segment the region of interest.

#### I. Segmentation of brain tumors

In the segmentation of brain tumors based on similar characteristics labels are assigned to each tissue. The brain is divided into different regions based on whether an area contains a tumor or not a tumor. When brain tumors are segmented, labels are given to tissue that has similar characteristics. The brain's regions that contain tumors and regions without tumors can be roughly separated. Then, the tissue within the tumor that has the same features can be further separated into subcategories, with each subcategory having a unique label. Each MRI slice has a label assigned to it, which is used to train and test the network. For better segmentation, these labels must be accurately applied [45]. Brain tumor segmentation is a technique for finding and separating brain tumors from healthy tissue in medical images, such as MRI scans. This process is crucial in determining the size, location, and treatment of brain tumors as it assists doctors in planning surgeries and other treatments [46].

- **Type of segmentation**

  i. **Unsupervised Brain Tumor Segmentation:** Unsupervised segmentation of tumors does not require labeled data. Instead, the algorithm looks for patterns and features in the images that are characteristic of tumors and uses these to identify and separate the tumors from the surrounding tissue. This approach is faster and does not require as much data, but it may be less accurate than supervised segmentation [45, 47]. The fundamental benefit of unsupervised techniques is that they don't need a labels dataset. In contrast to precise segmentation of tumor sections such as the enhancing tumor tumor core, unsupervised approaches are typically employed for an initial segmentation of the entire tumor region or an area of interest in brain tumor segmentation. Unsupervised learning techniques such as Fuzzy-C-means and SLIC were mostly used [48]. Due to the color similarity of brain tumors with other parts of the brain, these techniques are not very useful.

  ii. **Supervised Brain Tumor Segmentation:** Supervised brain tumor segmentation is a process where a machine learning algorithm is trained using a dataset of brain images that have been labeled by experts, who have identified and marked the location of tumors. The algorithm then uses this training data to learn to identify tumors in new images. This approach requires a large amount of labeled data and can be time-consuming, but it can produce highly accurate results [45, 47].In supervised learning techniques, labeled datasets are used for training and testing the algorithm that predicts the accuracy. In brain tumor segmentation and classification, mostly supervised learning techniques are used. In supervised learning, the algorithm first trains the datasets frequently and after that, makes accurate predictions on the data [47].

### 2.3.5 Classification of brain tumor

Deep learning is a machine learning approach that employs artificial neural networks to acquire knowledge and make decisions. It has demonstrated effectiveness in various fields, including medical image analysis, speech and image recognition, and natural language processing [49]. In the field of brain tumor classification, deep learning techniques are used to analyze medical images such as MRI scans, to classify the grade and type of brain tumors, which can be achieved through both supervised and unsupervised learning methods.

Convolutional neural networks (CNNs) are a type of deep learning algorithm that is commonly used for image classification purposes, including the classification of brain tumors [50]. CNNs are particularly well-suited to this task because they can automatically learn and extract features from images, such as texture, shape, and color, which are important for accurately identifying and classifying tumors. During the training process, the CNN is presented with a series of images and their corresponding labels (e.g., "glioma," "meningioma," etc.). It adjusts the weights and biases of its internal layers to reduce the error between the predicted labels and the true labels. Once trained, the CNN can be used to classify new images by making predictions based on the features it has learned to identify [51]. CNNs are effective for classifying brain tumors and their accuracy [51].

### 2.3.6 Segmentation and classification using Deep learning

Different CNN-based approaches have developed and proven effective in recent years at segmenting and classification of brain tumors. The methodologies may differ from one another in terms of the size and shape of the input, the size of the filter, the depth of the network, the connecting paths, etc.

### 2.3.7 Artificial Neural Networks

Artificial neural networks are computer-based systems that replicate the structure and function of the human brain. They are made up of interconnected "neurons" that process and transmit information [52]. There are several types of ANNs, including feedforward networks, convolutional neural networks (CNNs), and recurrent neural networks (RNNs). Feedforward networks consist of an input layer, one or more hidden layers, and an output layer. CNNs are specifically designed for image recognition tasks and include features such as convolutional layers and pooling layers [12].

The human brain is the primary decision-making organ. It has an extremely complex structure made up of billions of nerves that are interconnected to each other. The anatomy of the human brain makes it quicker and more powerful than any artificially created computer. It can quickly and efficiently address complex issues that no machine can manage while working in parallel. Biological research on the brain reveals that it has several layers of neurons coupled to one another to carry out activities requiring parallel processing. For the quick and precise processing of informational data, such as images, parallel processing is crucial. The human brain is incredibly good at quickly and accurately detecting and remembering images of things and people. The brain's billions of neurons are all interconnected to exchange information in the most efficient way possible. Each neuron exchanges information with the other neurons.

Strong decision-making abilities in the brain enable it to handle difficult tasks like motion detection and identification, arithmetic issues, and others. By storing all prior experiences and applying them to comparable issues, the human brain can solve similar problems. To develop artificial networks, scientists attempted to replicate the structure and operation of the brain on a computer. Similar to how the brain employs training and learning, this artificial network does as well. An Artificial Neural Network (ANN) is a complex mathematical algorithm that has three main components [53]. An Artificial Neural Network (ANN) consists of three main components: the input layer, the middle or hidden layers, and the output layer. The input layer receives signals and prepares them for processing by the hidden layers. The hidden layers perform most of the processing functions using neurons that apply mathematical operations to input data and produce various outputs. The output layer generates the final output for the network and plays a critical role in the network's training process by evaluating and comparing the generated data to the desired outcomes. During the learning phase, errors in the output layer are introduced and fed back to the earlier neurons.

### 2.3.8 Convolutional Neural Networks

The specific properties of CNNs are the main topic of this section provides basic CNN, a state-of-the-art network, which demonstrates convolution layers, pooling layers, and fully connected layers. There are no up-sampling layers in the network because it is a classification network.

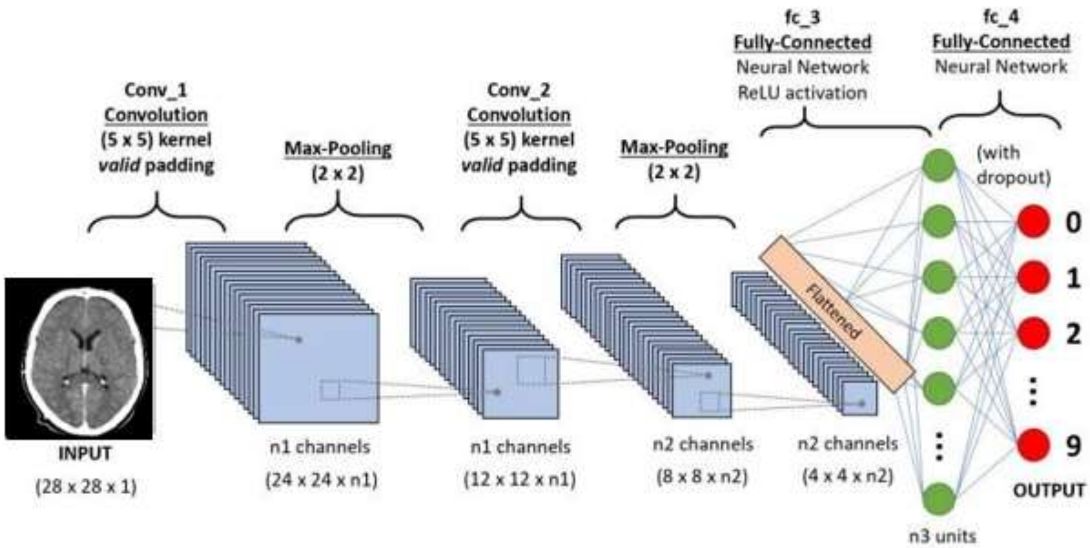


**Figure 2. 3.1:** CNN model [54]

Convolutional Neural Networks, also known as CNNs, are a type of neural network that has excelled in tasks like image identification and classification. Convolutional neural networks dominate computer vision techniques because of their precision in image classification.

Convolutional Neural Networks (ConvNets) use input images to incorporate specific features into the network's architecture. This results in a reduction in the number of parameters and an enhancement of the efficiency of the forward function implementation. Neurons that makeup ConvNets have biases and weights. Each neuron takes some inputs and executes a dot product. The architecture of convolutional neural networks differs from that of ordinary networks. In traditional neural networks, input is passed through multiple layers of hidden neurons. Each layer is composed of a group of neurons, and the neurons in each layer are fully connected to every neuron in the next layer. Additionally, the neurons in each layer operate independently of one another and do not share any connections. The final layer, the output layer, represents the network's predictions and is also fully connected [54, 55].

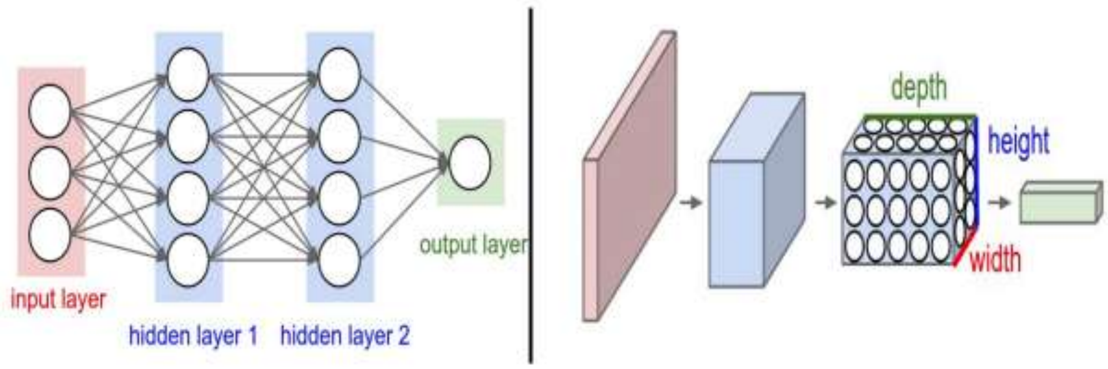


**Figure 2.3.2:** A Convolutional Neural Network and a Simple Neural Network [55]

In the above figure 3.3, the left side illustrates a conventional three-layer neural network, while the right side depicts a Convolutional Neural Network (CNN) that organizes its neurons in three dimensions (height, width, and depth) [54].

- **The Convolution Operation:** Convolution operation, a mathematical operation is performed in a convolutional neural network. Convolution is a mathematical operation that involves taking two functions (a and b) and producing a third function. It is represented by the symbol a*b and is calculated as the integral of the product of the two functions after one is flipped and moved.

$$(a * b)(t) = \int_{-\infty}^{+\infty} f\,(\tau)b(t - x)d\tau \qquad 2$$

The convolution operation involves three elements,

The input image is the image that is provided as input.

- **Feature detector**: The feature detector, also known as a "kernel" or "filter", is used to detect specific features in the image. It is commonly represented by a matrix, such as 5x5 or 7x7.
- **Feature map:** The feature map, also referred to as the activation map, is a representation of where a certain type of feature is present in the image. It is named feature map because it maps the location of specific features in the image
- **The Convolution Arithmetic:** The input factor that affects the output of a convolution is explained as [55]:

Suppose,

Image Input Size = N, (means width N and Height N i.e. image size is N * N)

Size of Filter = F, (Filter is F * F)

Number of Strides = S

Zero Padding = P

output image size will be: O

$$O = \frac{N-F+2P}{S} + 1 \tag{3}$$

- **Building Block of CNN Model:** A simple CNN consists of a series of layers, each of which uses a differentiable function to transform one volume of activations into another. There are three primary categories of layers used to create CNN architectures.

## I. Convolutional Layer

A convolutional layer is a crucial component of a Convolutional Neural Network (CNN) model. It operates convolution on the input image, using a set of filters or kernels. These filters are designed to detect specific features in the image, such as edges, textures, and patterns. Each filter is convolved with the input image, producing a feature map that represents the presence of the specific feature the filter is designed to detect. The output of multiple filters is then stacked to form a multi-channel feature map. These feature maps are then passed through one or more non-linear activation functions, such as ReLU, to introduce non-linearity into the model. The result is then passed to the next layer, which can be another convolutional layer or a pooling layer. This process is repeated until the final output is obtained.

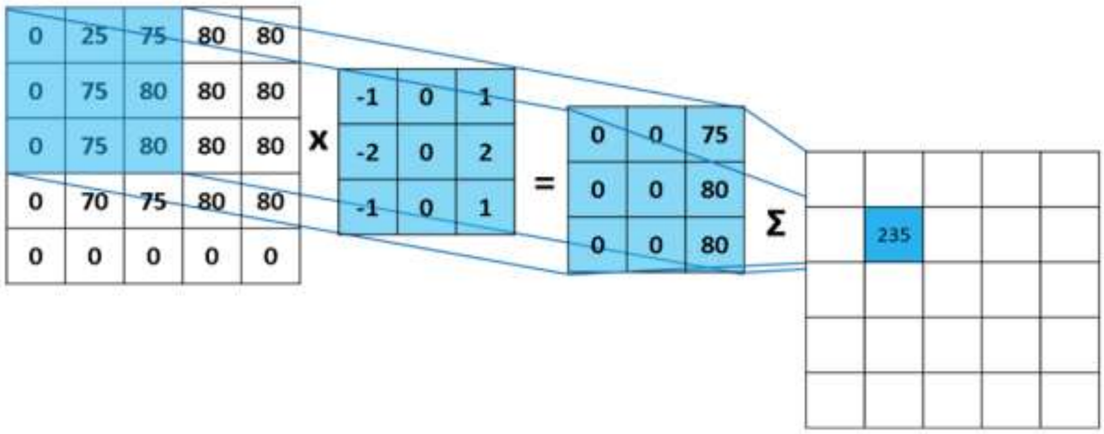


**Figure 2.3.3:** Convolution Operation of CNN [55]

The feature makes the computation more effective by decreasing the total number of parameters and making computation easier.

Following are the three parameters through which the output volume of the convolution layer is controlled.

- **Depth**: The depth of the input volume in the first layer of a CNN model represents the number of color channels in the input image. In the case of a colored image, the depth is 3, representing the red, green, and blue channels. If the image is grayscale or black and white, the depth is 1. The depth of the output volume is determined by the number of filters applied to the input image.
- **Stride:** Stride is used to move along the supplied image's width and height. One pixel at a time is moved by the filters when the stride is 1. When the stride is 2, the filters move around at a rate of 2 pixels for each movement.
- **Zero Padding**: Zero-padding is the technique through which padding the input image in the input layer with zero. The input layer's size can be managed by using zero padding. If zero-padding is not used, it's possible that some edge-related properties could be lost [54, 55].

## II. Pooling Layer

Pooling layers are utilized to decrease the size of feature maps by summarizing the features within a certain area, which in turn reduces the number of parameters that need to be learned. The pooling layer summarizes the features present in a region of the feature map generated by a convolution layer [55].

**i) Pooling functions**

The work of pooling is completed by reducing the input parameters by using various techniques, such as taking the average, minimum, or maximum value of the sub-regions only.

- Kinds of Pooling Functions: Following are the different kinds of pooling functions.

- *Max Pooling*: This operation returns the highest value possible.
- *Average Pooling*: It takes the average and returns the highest value.
- *Weighted Average Pooling*: Based on the pixel's distance from the center, it determines the neighborhood weight.
- *L2 Norm Pooling*: It returns the square root of the neighborhood's rectangles.

Max Pooling is utilized in the majority of ConvNet architectures to reduce computational costs [55].

## III. Fully-Connected Layer

Similar to a neural network, every neuron in the fully connected layer is connected to every other neuron in the layer below it. Its activation is calculated using matrix multiplication with weight and bias [55].

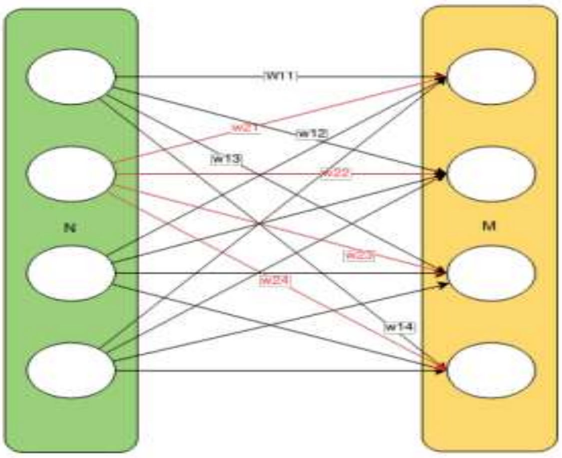


**Figure 2.3. 4:** Fully Connected Layer of CNN [54]

### 2.3.9 Activation Function

An Activation Function decides whether a neuron should be activated or not. This indicates that it will determine using more basic mathematical operations whether the neuron's input to the network is significant or not.

Commonly used activation functions are.

#### I. ReLU (Rectified Linear Unit)

Rectified Linear Unit is referred to as ReLU. It sets the input value's threshold to zero. It returns the number when it is positive and zero when it is negative. ReLU was 6 times faster than the function in Alex Net architecture after being used as an activation function. The following is the ReLu formula [55]:

$$f(x) = max(0, x) \tag{4}$$

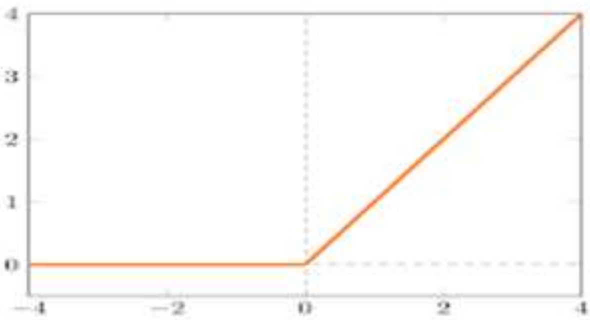


**Figure 2.3. 5:** Curve of ReLU Function [55]

**The benefits of using the ReLU function include:**

1. Its computational efficiency enables the network to quickly converge.
2. Its non-linearity, despite appearing linear in shape
3. Its ability to be used in backpropagation is due to the existence of its derivative function.

## II. Softmax

A softmax activation function is a generalization of the logistic function to multiple classes. Given an input vector, the function returns a probability distribution over all possible classes. This is useful in multi-class classification problems, where the target is to assign an input to one of several possible classes. The output layer of multilayer neural networks designed to perform classification tasks typically uses the softmax function (Equation 3.10). It calculates the probability of each class. The sum of all softmax results in an output layer equals 1. Softmax predicts which class the input most likely belongs to rather than making a precise choice between classes.

Mathematical representations of the softmax function are as

$$\text{softmax}(x) = \frac{e^{x_k}}{\sum_{i=1}^{m} e^{x_i}} \qquad 5$$

This function is commonly used as the final layer in a convolutional neural network (CNN) that is being used for image classification. The output of the final layer is a probability distribution over all classes, and the class with the highest probability is chosen as the prediction of the network [56].

A CNN consists of several layers of convolutional and pooling layers, followed by one or more fully connected layers, and at the end the softmax layer. The convolutional and pooling layers extract features from the input image, and the fully connected layers combine these features to form a compact and informative representation of the image. The softmax layer then produces a probability distribution over all classes, which can be used to make a prediction [57].

## III. Sigmoid

Artificial neural networks, such as convolutional neural networks, frequently used the sigmoid activation function. It is a type of squashing function that maps any input value to a value between 0 and 1. This makes it useful for modeling binary outcomes, such as classifying an input as belonging to one of two classes, or for modeling probability.

The mathematical representation of the sigmoid function is

$$S(A) = \frac{1}{1+e^{-a}} \quad 6$$

Where x is the input to the activation function. The sigmoid function has a smooth transition between 0 and 1, which helps the neural network to converge better during the training process.

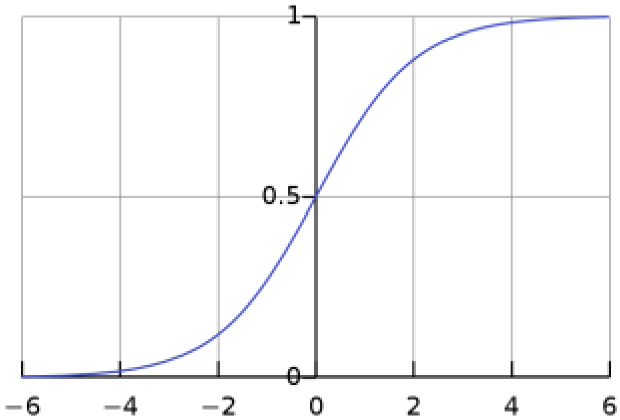


**Figure 2.3. 6:** Curve of a sigmoid function [55]

When a CNN is used for binary classification, the sigmoid function is frequently utilized as the activation function for the output layer [55].

### 2.3.10 U-Net

The U-net is a neural network architecture designed specifically for medical image segmentation. It is composed of two main parts: the contracting path, also referred to as the encoder or analysis path, and the expansion path, known as the decoder. The contracting path functions similarly to a traditional convolutional network. On the other hand, the expansion path, which uses up-convolutions and concatenations with features from the contracting path, increases the resolution of the output. Finally, the output passes through a convolutional layer to produce a fully segmented image. The U-net's symmetry and shape resemble the letter U [58].

## I. Basic U-Net

The U-net network consists of two parts: the contracting path and the expansive path. Contracting path, which follows a standard CNN architecture. A max-pooling layer, a ReLU activation unit, and two successive 3x3 convolutions make up each block of the contracting path. The uniqueness of the U-net is seen in the second section, referred to as the expansive path, where each stage uses 2x2 up-convolution to increase the resolution of the feature map. After that, the up-sampled feature map is concatenated with the feature map from the appropriate layer in the contracting path.

The segmented image is created at the end of the process by applying an additional 1x1 convolution on the feature map to reduce it to the necessary number of channels. Since pixel properties on the boundaries contain the least amount of contextual information, they must be removed, therefore requiring cropping. This creates a network with a U-shape appearance and, more crucially, spreads context-specific information throughout the network, allowing it to segment objects using context from a wider area [58].

## II. 3D U-net

The 3D U-net is a variation of the U-net framework that enables 3D volumetric segmentation. It maintains the contracting and expanding path of the original U-net, but replaces 2D operations, such as convolutions and pooling, with their 3D equivalents. This allows the network to segment 3D images with a high degree of accuracy, even when trained on a limited number of labeled samples. This is due to the presence of repeating structures and shapes within 3D images, which can be easily learned with minimal training data.

### 2.3.11 Regularization Function

Regularization is the process of normalizing machine learning models to reduce the adjusted loss function and avoid overfitting or underfitting. A basic model may underperform due to inadequate generalization, while a complex model may underperform due to over-fitting. In this situation, regularization help in selecting the model's preferred level of complexity [59]. Dropout and Batch Normalization are the two primary regularization methods.

- **Dropout:** Dropout is a regularization technique. It works by randomly setting a fraction of the input units to zero during training, which helps to prevent overfitting and improve the generalization of the model. Dropout briefly removes some of the neurons during the forward pass. For example, one out of every five neurons, for instance, will be deactivated during the forward pass if dropout is set to 20%. Any weight update won't be applied to these neurons during the backward pass [59, 60].
- **Batch Normalization**: Batch normalization is a method for normalizing a system to improve its performance. It works by normalizing the activations of each layer in a batch of input data. This helps to prevent the problem that occurs when the distribution of the activations of a neural network changes during the training process [60].

### 2.3.12 Optimizer

ADAM is an optimization algorithm that adjusts the parameters of a machine learning model in a way that improves its performance [61]. It is a variation of the stochastic gradient descent algorithm( SGD), and it is well-suited for training deep learning models.ADAM algorithm uses a combination of two moving averages: one for the gradients and another for the squared gradients. It uses these averages to estimate the first and second moments of the gradient, which it then uses to update the model parameters. One of the main benefits of ADAM is that it requires less tuning of the learning rate compared to SGD, as it adapts the learning rate automatically during training [61, 62].

### 2.3.13 Evaluation metrics

The evaluation of the segmentation network is a critical step in determining a network that is capable of segmentation. Performance can be assessed using a variety of criteria, but it essentially measures how closely the network's output matches the real world. The dice coefficient and accuracy are two evaluation metrics that are frequently applied to the segmentation task. Accuracy and loss are two common evaluation metrics used in machine learning and deep learning [63].

- **Accuracy**

Accuracy is the fraction of correct predictions made by the model, concerning the total number of predictions made [63]. It is commonly used in classification tasks, and can be calculated as follows:

This is formulated mathematically in the equation

$$\text{Accuracy} = \frac{\text{Correctly classified samples}}{\text{Total number of sample}} \tag{7}$$

- **Loss function**

Loss is a measure of how far the predictions made by the model are from the true values. It is commonly used in both classification and regression tasks and is used to optimize the model during training [18, 21] There are many loss functions available, and the choice of loss function depends on the task at hand.

- **Dice coefficient**

Dice coefficient, which is simply an assessment of sample overlap. The Dice coefficient, which spans from 0 to 1, represents perfect and total overlap. Initially designed for binary data, the Dice coefficient can be calculated as [64].

$$DCS = \frac{2|A \cap B|}{|A| + |B|} \tag{8}$$

## 2.4 Summary

In this chapter, total 24 research papers are analyzed along with their techniques. This assessment of the literature demonstrates that there have been numerous research papers published on the segmentation and classification of brain tumors. Several researchers used standard classifiers, while others used deep learning techniques. Mostly focused on those articles that used deep learning techniques. Some works obtained a significant outcome utilizing various methodologies, whilst others did not. However, after reviewing this research, it is conclude that deep learning techniques perform better than other techniques.

This chapter also provides a brief overview of each topic that is relevant to our thesis work, along with information on how they operate, their benefits and drawbacks, etc. First, attempted to outline the subjects of fundamental digital image processing, image segmentation, and brain tumor classification. The artificial neural network was then discussed, followed by a breakdown of the fundamental CNN design, its several hyper-parameters, the U-Net architecture, and the 3D U-Net architecture. After that, explained different activation functions and evaluation metrics.

# CHAPTER 3

# DATASET AND IMPLEMENTATION

## 3.1 Overview

In this section, the techniques for segmenting and classifying brain tumors using deep learning are described. Preprocessing of the MRI images, the dataset and software used, segmentation and classification approaches, and their architecture will all be covered in this chapter. The final section of the chapter will examine how experiments involving various networks and the result of the experiment will also describe.

## 3.2 Datasets

Datasets play a crucial role in the development and evaluation of algorithms for brain tumor segmentation and classification. The use of datasets in brain tumor segmentation and classification allows for the development of automated and objective methods to assist medical professionals in the diagnosis and treatment of brain tumors. These methods can help reduce inter-observer variability, provide more accurate tumor delineation, and assist in the selection of appropriate treatment strategies.

The BRATS (Brain Tumor Segmentation) datasets are a collection of medical imaging data that includes Magnetic Resonance Imaging (MRI) scans of the brain with gliomas, which are a type of brain tumor. The purpose of these datasets is to support the development and evaluation of algorithms for brain tumor segmentation and classification. The BraTS challenge consists of several routinely acquired preoperative multimodal MRI scans of lower-grade glioma (LGG) and glioblastoma (HGG) from multiple institutions that have a pathologically verified diagnosis. BraTS'18, the datasets used for the competition have been updated with more frequently collected 3D multimodal MRI images from clinical sources with ground truth labeling by experienced board-certified neuroradiologists. The Kaggle website is used to download the dataset [65-67].

This section examines the dataset used for training and testing the segmentation and classification of brain tumors.

### 3.2.1 MICCAI BraTS data

The MICCAI BraTS training dataset from 2019 contains 335 patients with 4 different modalities which are T1, T2, T1CE, and Flair. There are 335 patient cases in the BraTS 2019 Dataset, consisting of 259 patients with HGG (high-grade gliomas) and 76 individuals with LGG (low-grade gliomas). Each directory consists of four information channels related to four separate volumes of the same location that were acquired using various imaging methods. These channels include:

1. Native (T1): Using a T1-weighted imaging approach, this channel offers details on the tissue density and structure of the area.
2. Post-contrast T1-weighted (T1CE): This channel is comparable to the original T1, but by applying a contrast agent, it gives more details about the tissue.
3. T2-weighted (T2): This channel uses a T2-weighted imaging approach to offer details on the tissue composition and fluid levels in the area.
4. T2 Fluid Attenuated Inversion Recovery (FLAIR) volumes: This channel is identical to the T2 channel, but by employing a particular inversion recovery technique, it offers extra information on the fluid content in the region.

Labels usually referred to as annotations, are used to distinguish between various areas or characteristics within an image. All of the images are divided into four groups:

Label 0: Unlabeled volume, indicating that the region is unimportant or unrelated to the analysis.

Label 1: The necrotic and non-enhancing tumor core (NCR/NET) is labeled as the region of the image where the tumor does not show any enhancement.

Label 2: This label designates the region of the image where the tumor is surrounded by edema (swelling).

Label 3 is missing (there are no pixels with label 3 in any of the volumes), which means that there is no image with it.

Label 4: GD-enhancing tumors (ET) designates the region of the picture where the tumor is enhancing.

**Table 3. 1:** Intensity for different brain tissue in respective modalities

| Tissues | Flair | T1 | T2 | T1CE |
|---|---|---|---|---|
| Fat(within bone marrow) | Light | Bright | Light | Bright |
| Cortex | Light Gray | Gray | Light Gray | Bright |
| Inflammation(infection, demyelination) | Bright | Dark | Bright | Bright |
| White Matter | Dark Gray | Light | Dark Gray | Dark |
| CSF | Dark | Dark | Bright | Dark |

An example of a brain tumor is given below.

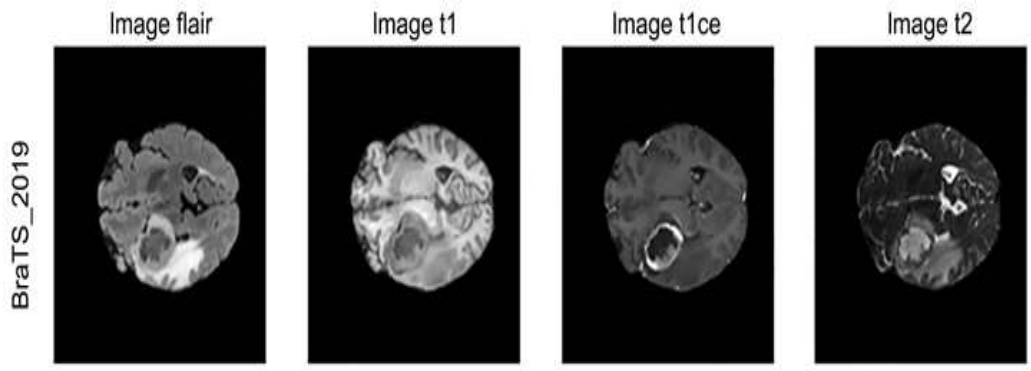


**Figure 3. 1:** An example of a brain tumor

### 3.2.2 Training and Testing Datasets

MICCAI_BraTS2019 Data contains 335 are split into two groups as shown in table 3.2 where training data consist of 75% and 25% of data are in testing datasets.

**Table 3. 2:** Table with an explanation of data split and the chosen split sizes

| Data portion | Explanation | split % | No.of images |
|---|---|---|---|
| Training data | The part of the data with which the model is trained with | 75% | 195 |
| Testing data | The part of the data which is used for testing purposes | 25% | 65 |

The size of Every image is (240 X 240). Four images, including Flair, T1, T1ce and T2 images, were taken from a single subject. BraTS19 2013 is the patient ID. These four images, taken using four separate modalities, show that the tumor's location and the outline of the tumors can be seen in the T1 and T2 modalities. The brain tumor can be generally identified in the Flair modality. However, in these two images of the modality T1, brain tumors are rarely visible.

### 3.2.3 Imbalanced data

The training data is quite imbalanced as most of the area of the images contains data that are not required.

As the equation of finding the number of training slices are

Number of training slices = number of slices X number of training images

To reduce class imbalance and complexity of the network all images in the training datasets are resized from the original size of 240 × 240 to 128 × 128. For making computation easier and to reduce computational time Min-max scalers are used.

## 3.3 Software and Libraries

### 3.3.1 Tensor Flow

The Google Brain team originally released TensorFlow [65] to the public in 2015. TensorFlow is a free and open-source software framework for creating and deploying machine learning algorithms. It is made to be extremely scalable and enables computations to be run on many CPUs and GPUs simultaneously for improved performance. Python and Java are only a couple of the many programming languages that make it simple to access and manage TensorFlow. One of the most popular machine learning libraries, due to its usability, accessibility, and performance. Additionally, Keras, a high-level neural networks API that runs on top of TensorFlow, may be built upon TensorFlow as a basis for additional libraries.

### 3.3.2 Keras

Keras is a Python-based high-level neural network API that may be used in combination with TensorFlow [68] Its simple design, flexibility, and user-friendly interface make it simple to experiment with and develop machine learning models rapidly. Keras is built on TensorFlow, which allows it to operate effectively and flexibly on a wide range of CPUs and GPUs. This makes it a popular tool for constructing and testing neural network models among academics and developers. Model definition and training are made simple with Keras, which may also be used to execute previously learned models.

### 3.3.3 3D Slicer

An open-source programed called 3D Slicer can be used to visualize and edit medical pictures. 3D Slicer is a powerful platform that is widely used in many medical fields for the pre-processing and post-processing of images. The platform provides a wide range of apps created and maintained by its user community. It is a helpful tool for evaluating and understanding medical images since it can show image data in 2D and 3D formate.

## 3.4 Implementation

This section explain each step of implementation. In the implementation step,data was prepared by using preprocessing steps. After pre-processing the datasets, 3D u-net was applied for the segmentation of the brain tumor. At last, 3D CNN was applied for the classification of tumors into HGG and LGG.

### 3.4.1 Data Pre-processing

To make computational operations easier, data preparation must be applied to the existing data set before beginning training. Data analysis cannot be done directly because there are so many conflicting, missing, and unclean data sources in the real world, which may affect the result analysis. Different preprocessing techniques are applied to enhance the result. Data preprocessing is often referred to as attribute value normalization. Preprocessing the attribute value before training is typically necessary. To increase the attribute value following the transformation of the scheme with the best performance under any attribute, the data must be preprocessed.Various techniques such as min-max scaler and image resize techniques are used to prepare data. Data cleaning procedures are used to fill in missing values, eliminate noise from the data, identify abnormalities, and reduce disputes. The main objectives include removing abnormal data, removing errors, and removing duplicate data. The absolute path i.e. a path that contains the entire path to the file or directory of the MRI image must first be identified before moving on to the data pre-processing stage. The image's pixel data can only be read and written in the correct array using the absolute path. Reading image data and converting image data into arrays respectively call two functions in Reading image data and converting image data into arrays call two functions in ‘nib. Load’ and ‘get_fdata ()’. The first function is used to obtain image data, and the second function is used to convert image data into array data for storage. The MRI images must first be cropped after the preparation steps. Because every MRI scan of a brain tumor contains a considerable amount of data with a pixel value of zero. Blank spaces must be removed. On the other hand, the region with a 0-pixel value occupies a substantial portion of some MRI image slices with a tiny brain image area, which will also have an impact on the model's prediction of the result. To decrease their impact, each slice must be chopped during preprocessing and the blank pixels must be eliminated.To reduce the size of the MRI image, the original (240 X 240) MRI image was cropped into a new image with a specification of (128 X 128).

The BraTS multimodal scans are available as NIfTI files (.nii.gz). The volumetric dimension of all dataset MRI scans (T2,FLAIR, T1, and T1ce) is 240X240 voxels.By combining T2,T1ce and FLAIR images,make 3D volumetric data. Images are downsized to 128 X 128 X 128 voxel size to reduce unnecessary empty areas surrounding the relevant volume of interest. The code in Figure 3.2 shows how this project normalizes and crops the image data.

```
for img in range(len(t2_list)):   #Using t1_list as all lists are of same size
    print("Now plist[ireparing image and masks number: ", img)

    temp_image_t2=nib.load(t2_list[img]).get_fdata()
    temp_image_t2=scaler.fit_transform(temp_image_t2.reshape(-1, temp_image_t2.shape[-1])).reshape(temp_image_t2.shape)

    temp_image_t1ce=nib.load(t1ce_list[img]).get_fdata()
    temp_image_t1ce=scaler.fit_transform(temp_image_t1ce.reshape(-1, temp_image_t1ce.shape[-1])).reshape(temp_image_t1ce.shape)

    temp_image_flair=nib.load(flair_list[img]).get_fdata()
    temp_image_flair=scaler.fit_transform(temp_image_flair.reshape(-1, temp_image_flair.shape[-1])).reshape(temp_image_flair.shape)
    temp_mask=nib.load(mask_list[img]).get_fdata()
    temp_mask=temp_mask.astype(np.uint8)
    temp_mask[temp_mask==4] = 3  #Reassign mask values 4 to 3
    #print(np.unique(temp_mask))


    temp_combined_images = np.stack([temp_image_flair, temp_image_t1ce, temp_image_t2], axis=3)

    #Crop to a size to be divisible by 64 so we can later extract 64x64x64 patches.
    #cropping x, y, and z
    temp_combined_images=temp_combined_images[56:184, 56:184, 13:141]
    temp_mask = temp_mask[56:184, 56:184, 13:141]

    val, counts = np.unique(temp_mask, return_counts=True)

    if (1 - (counts[0]/counts.sum())) > 0.01:  #At least 1% useful volume with labels that are not 0
        print("Save Me")
        temp_mask= to_categorical(temp_mask, num_classes=4)
        np.save('/content/Datasets/BraTs2019_TrainingData/input_data_3channels/images/iskmage_'+str(img)+'.npy', temp_combined_images)
        np.save('/content/Datasets/BraTs2019_TrainingData/input_data_3channels/masks/ma_'+str(img)+'.npy', temp_mask)

    else:
        print("I am useless")
```

**Figure 3.2**: Code for Preprocessing

### 3.4.2 Segmentation steps

After preprocessing, the next step of the experiment is segmentation. Segmenting a brain tumor is the process of separating the tumor from healthy brain tissue; in typical clinical practice, this information is helpful for diagnosis and treatment planning. However, given the irregular shape and unclear boundaries of tumors, it is still a difficult process [66].

For accurate segmentation of brain tumors, we used 3D-Unet. The architecture of our 3D-unit model will be explained below.

## I. 3D-u-net Architecture

Up-sampling layers and down-sampling layers make up the U-Net design. The down-sampling layers follow the conventional convolutional neural network design in that each convolutional layer is followed by a linear rectification layer and a max-pooling 3D operation, with the same padding and a dropout of 0.1. Thus, after each stage of the first half, the number of image channels doubles. Then, each step of the up-sampling section consists of two 3 3 convolutions, a linear rectification layer, and a dropout of 0.2, followed by a Conv3D Transpose 3D convolution and a concatenation with the appropriate feature map from the first part. U-Net is very useful in biomedical imaging.

Fig.3.3 shows the architecture of our 3D-unit model. The architecture receives a 128x128x128 voxel input image and produces an image of the same size. An encoder and a decoder are components of the architecture. Several layers make up the encoder, including, two 3x3x3 convolutional layers with ReLU as activation functions. To preserve more information, the encoder additionally has a down-sampling layer that uses a 3x3 convolution with step size 2. The lowest layer of the encoder's output feature map has a dimension of 256x8x8x8. Compared with the input, the number of channels increases from 16 to 256, and the size of the feature map is decreased by 8 times. The network's decoder is made up of the output layer and four blocks. The number of channels decreases as you move up the decoder, while the size of the feature maps gradually increases. The decoder uses transpose 3D to execute three up-sampling from the bottom to the top. The output layer sits on top of the decoder and is composed of a softmax activation function and a 1 X 1 X 1 convolution layer. The output layer's feature map has the same size as the input image. An input for a decoding block is created by concatenating the output feature maps from previous decoding blocks that have been upsampled with the output feature maps from the appropriate level of the encoder during the decoding process.

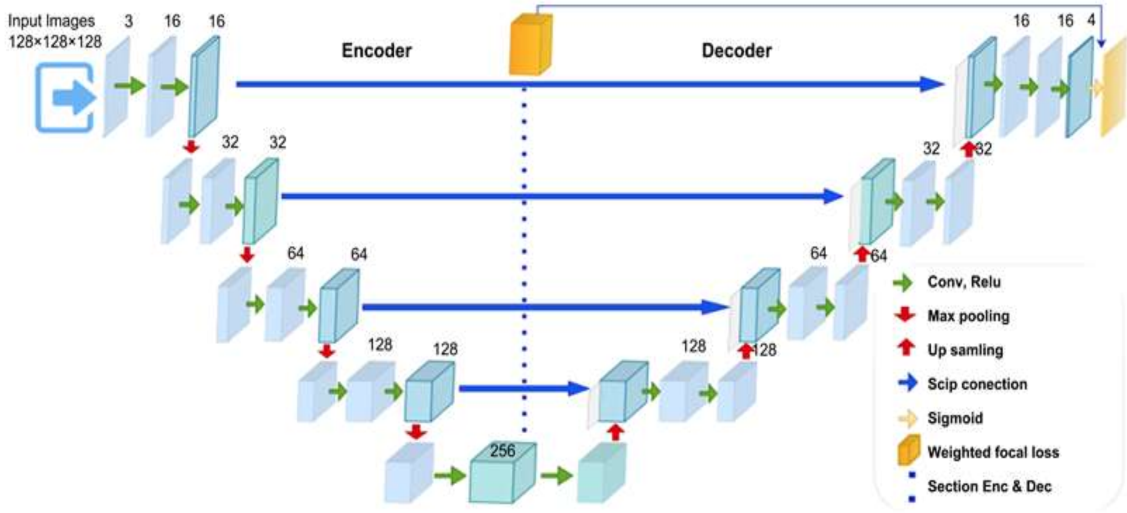


**Figure 3. 3:** 3D-unit architecture

My research generally employed a model for 100 epochs with 4 channels measuring 128 x 128 x 128 voxels, a batch size of 2. The parameters used during the training procedure are described in Table 3.3. Our work uses Adam, an adaptive first-order gradient-based optimization method, with a learning rate of 0.0001, which is generally superior to all other optimization algorithms and has a faster calculation time One of the often used activation functions in binary image segmentation models is the sigmoid; in a network, the prediction segmentation result of the target image is generated using a final convolutional layer with softmax activation after the last linear block in the up-sampling path.

**Table 3. 3:** Components of the training model

| Name | Value |
|---|---|
| Input size | 128X128X128 |
| Batches | 2 |
| Optimizer | Adam |
| Epoch | 100 |
| Activation | Sigmoid |

### 3.4.3 Classification steps

After brain tumor segmentation the next step is to classify the brain tumor. Therefore, the effectiveness of the final tumor classification is influenced by the precision of brain tumor segmentation. Deep learning 3D CNN is used for classification. In this section, we will explain 3D CNN and the result is the classification.

### I. Proposed Approach

The proposed approach includes essentially the following steps:

1. Data Preprocessing.
2. Data Augmentation.
3. Split data into training and testing.
4. 3D CNN models are used for the classification of brain tumors.

i. **Data Preprocessing :** In the preprocessing steps, first, I collect all the segmented images after the segmentation steps. After segmentation, of both HGG and LGG datasets, all the segmented images are collected and made data ready for training 3D CNN model.

ii. **Data Augmentation :** In deep learning-based image classification, data augmentation is a common method for modifying existing data samples to enhance the performance of models. This can enhance the model's capacity and avoid overfitting. Random flipping, rotation, scaling, and cropping are a few typical methods for data augmentation in image classification [67]. In this code, we apply the data augmentation technique of rotation. Specifically, it rotates the data by angles of 0, 90, 180, and 270 degrees using the rotate function. It then saves the augmented data as new .npy files in the augmented data directory. The number of augmented versions to create for each original data point is specified by the num_augmentations variable which is case 4, and the rotation angles are specified by the rotation_angles variable.

iii. **Splitting the Datasets:** To make data ready we split the datasets into training and testing. 20% of the datasets are for testing purposes and 80% of the datasets are for training purposes. The datasets contain a total of 550 MRI images.

Table 3.4 shows the training and testing datasets of the model.

**Table 3. 4:** Training and Testing data

| Data Portion | Explain | Split % | Number of images |
|---|---|---|---|
| Train Datasets | The portion of the data with which the model is trained with | 80 | 440 |
| Test Datasets | The portion of the data with which the model is tested with | 20 | 110 |

Table 3.5 show the component of our model, which include image input size, batch size, optimizer used, the total number of epoch, and the activation function.

**Table 3. 5:** Component of our training model

| **Name** | **Value** |
|---|---|
| Input size | 128X128X128 |
| Batches | 2 |
| Optimizer | Adam |
| Epoch | 100 |
| Activation | Sigmoid |

iv. **3D Convolutional Neural Network Architecture:** Instead of using a 2D-CNN architecture, which only explores two-dimensional slices of the volumetric information in MR images, we use a 3D convolutional layer, which generates a detailed feature map by utilizing the full volumetric spatial information.

A 3D CNN model is a type of convolutional neural network that is specifically designed to process 3D data, such as videos, 3D images, or 3D point clouds. It is composed of several layers, each of which performs a specific function in the overall process of feature extraction and classification.

The first layer of a 3D CNN model is typically a convolutional layer, which is responsible for extracting features from the input data. This layer is followed by one or more additional convolutional layers, which help to extract increasingly complex features as the model progresses through the layers.

After the convolutional layers, the 3D CNN model may include one or more dense layers, which are fully connected layers that are responsible for classifying the extracted features. These dense layers are typically composed of a large number of neurons, and they use these neurons to make predictions based on the input data.

The model also has a flattened layer, which is used to flatten the output of the convolution and dense layers into a single vector of data that can be processed by the final layer of the model. This allows the model to take the output of the convolution and dense layers and turn it into a single set of data that can be used for classification or prediction.

Finally, the model has a dropout layer with a dropout rate of 0.5. Dropout is a technique that is used to prevent overfitting in neural networks. It works by randomly dropping out a certain percentage of the neurons in the model during training, which helps to prevent the model from becoming too specialized or too reliant on any particular set of input data. This can help to improve the generalization ability of the model and make it more robust to changes in the input data.

Fig. 3.4 shows the summary of the 3D CNN architecture, which is made up of three convolutional layers and two fully connected (FC) layers.

```
from types import CodeType
from keras.engine import sequential
from keras import models
#Model building

model=Sequential()
model.add(Conv3D(32, (3,3,3), input_shape=(128,128,128,1)))

model.add(Activation('relu'))
model.add(MaxPooling3D(pool_size=(2,2,2)))

model.add(Conv3D(32,(3,3,3), kernel_initializer='he_uniform'))
model.add(Activation('relu'))
model.add(MaxPooling3D(pool_size=(2,2,2)))

model.add(Conv3D(64,(3,3,3),kernel_initializer='he_uniform'))
model.add(Activation('relu'))
model.add(MaxPooling3D(pool_size=(2,2,2)))

model.add(Flatten())
model.add(Dense(64))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(1))
model.add(Activation('sigmoid'))

model.compile(loss='binary_crossentropy' , optimizer='adam', metrics='accuracy')


model.save('BrainTumormodelh5.h5.')

model.summary()
```

**Figure 3. 4:** Proposed 3D CNN model

The research generally employed a model for 100 epochs with 4 channels measuring 128 x 128 x 128 voxels, a batch size of 2. The parameters used during the training procedure are described in Table 3.6.

**Table 3.6:** Component of Classification training model

| **Name** | **values** |
|---|---|
| Input size | 128 × 128 × 128 |
| Batch size | 2 |
| Epochs | 100 |
| Optimizer | Adam |
| Activation | sigmoid |

## 3.5 Summary

This chapter describes the proposed methods for classifying and segmenting brain tumors. The segmentation and classification of brain abnormal tissues by two distinct processes are thoroughly demonstrated with appropriate diagrams and explanations.Also explain the preprocessing steps,segmenation setps and classification steps alongwith their steps.

# CHAPTER 4

# RESULTS AND ANALYSIS

## 4.1 Overview

This chapter, present the results of deep learning approach for accurately detecting and identifying brain tumors in medical images.The research purpose is to evaluate the performance of the 3D U-Net model for segmentation and the 3D CNN model for classification, as well as to assess the overall accuracy achieved by the proposed method. The BraTS 2019 dataset is utilized, which consists of 335 patient reports, including 76 cases of low-grade gliomas (LGG) and 259 cases of high-grade gliomas (HGG). Each MRI image in the dataset comprises four T1-weighted sequences (T1), T2-weighted (T2), FLAIR, and T1 with gadolinium-enhanced contrast (T1c).

## 4.2 Pre-processing Results

In the preprocessing steps the size of the MRI image, the original (240 X 240) MRI image was cropped into a new image with a specification of (128 X 128).The BraTS multimodal scans are available as NIfTI files (.nii.gz). The volumetric dimension of all dataset MRI scans (T2,FLAIR, T1, and T1ce) is 240X240 voxels.By combining T2,T1ce and FLAIR images,make 3D volumetric data. Images are downsized to 128 X 128 X 128 voxel size to reduce unnecessary empty areas surrounding the relevant volume of interest.

## 4.3 Results of Segmentation

The first step in the analysis is to evaluate the performance of the 3D U-Net model for segmentation. The 3D U-Net was trained to precisely segment brain tumors tissues from the surrounding healthy tissue, to isolate the region of interest for further analysis.

This section illustrates the results of segmentation for both HGG and LGG glioma tumors.

### 4.3.1 Results of Segmentation on BesTs 2019

The first step after preprocessing involved the utilization of the 3D U-Net model, which exhibited exceptional performance in segmenting the brain tumor from the surrounding tissue, effectively isolating the region of interest for further analysis. compelling evidence of the 3D U-Net's ability to precisely delineate brain tumors with better accuracy.The results are presented and plotted in Table 3.1 below. Primarily combine T1c, T2, and FLAIR and then train and test through the models.The 3D U-Net model trained on the BraTS 2019 dataset and performed segmentation on both the HGG and LGG tumor images. The segmentation results were quantitatively evaluated using accuracy and loss metrics. The findings of this study are shown in Table 4.1, the table provides accuracy for the model. The segmentation accuracy achieved impressive values of 98.9% for HGG and 95.5% for LGG tumors.

**Table 4. 1:** Segmentation Accuracy result of HGG and LGG data

| **DATA** | **DATA SETS** | **Accuracy** |
|---|---|---|
| HGG | BraTS 2019 | 0.989 |
| LGG | BraTS 2019 | 0.955 |

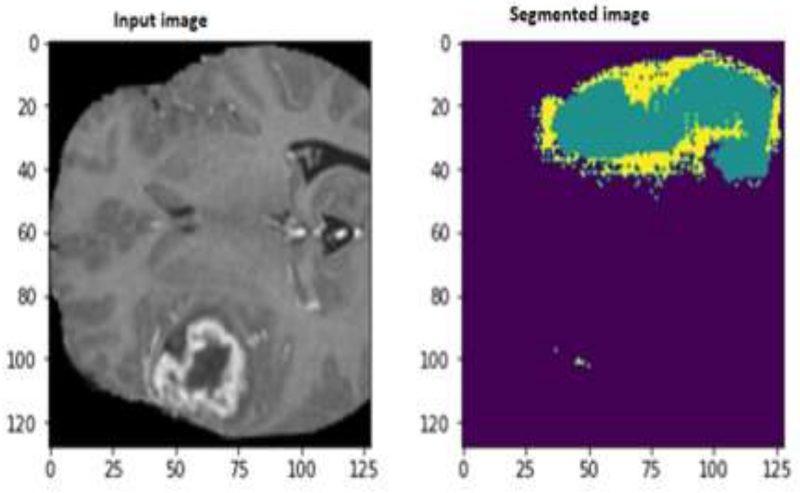


**Figure 4. 1:** Segmented MRI images

## 4.4 Result of Classification

After completion of the segmentation phase, the segmented images were then fed into the 3D CNN classifier, an integral component designed to categorize the brain tumors into their respective types. The results of this phase, with the 3D CNN achieving an accuracy of 96% in accurately classifying various tumor types. Such a remarkable accuracy rate reinforces the 3D CNN's robustness and proficiency in discerning between different tumor categories based on the segmented images.

The classification accuracy of the proposed model is 96%. Table 4.2 represent the accuracy of this model. It also shows the comparison of results with other models of paper [25, 40].

**Table 4. 2:** Classification Accuracy of models

| **Reference** | **Methodology** | **Accuracy** |
|---|---|---|
| [25] | 2D-Unit model for brain tumor segmentation and classification purposes SVM classifiers were used | Segmentation accuracy was 93% and Classification Accuracy was 91% |
| [40] | For brain tumor segmentation, the 3D U-net model was used, and used CNN model for the classification | The accuracy of the framework was 90%. |
| Proposed model | For brain tumor segmentation, a 3D U-net model was used followed by a 3D CNN model for classification | 96% |

To provide a visual representation of the classification performance, Figure 4.2 displays an accuracy graph of the proposed 3D CNN model. The model exhibits consistent and high accuracy throughout the training process, further confirming its effectiveness in classifying brain tumors.

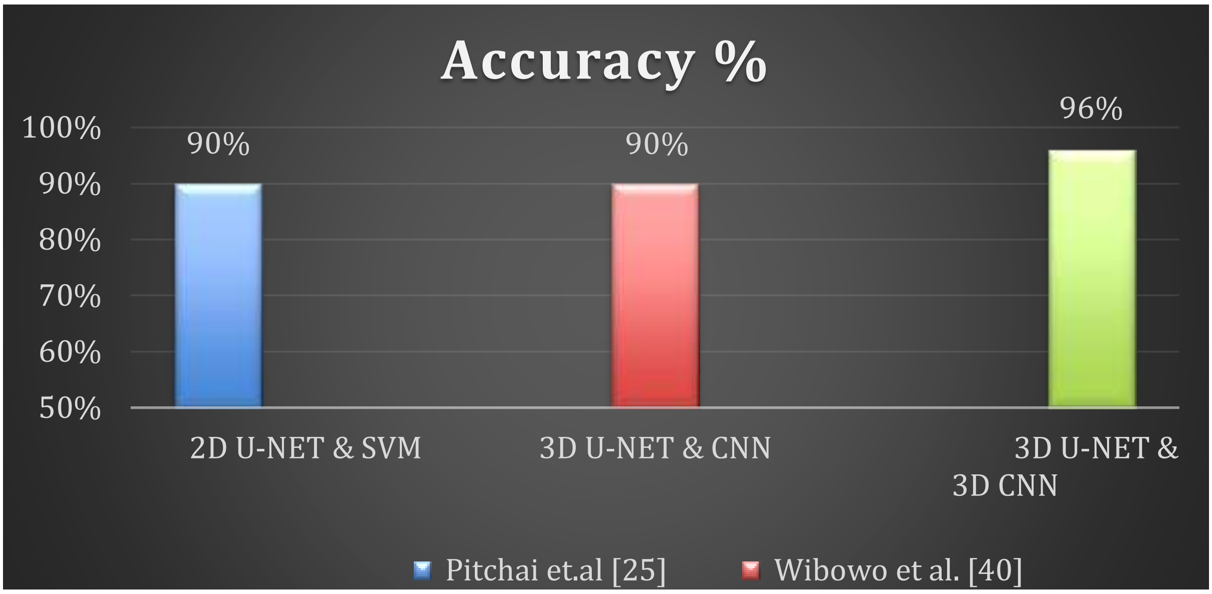


**Figure 4. 2:** Classification Accuracy graph of proposed model

## 4.5 Analysis of Results

The research aimed to address the problem of accurately detecting and identifying brain tumors in medical images with the ultimate aim of improving patient outcomes and facilitating more effective treatment decisions. The combination of these two methodologies holds great promise for revolutionizing the field of medical imaging analysis and transforming brain tumor diagnosis and treatment. To accomplish this, a deep learning approach was employed, utilizing two main techniques: 3D U-Net for segmentation and 3D CNN for classification. The 3D U-Net was trained to segment the brain tumor from the surrounding tissue, to isolate the region of interest for further analysis. The segmentation performance was evaluated using the accuracy of 98% was achieved. This high accuracy indicates that the 3D U-Net was able to effectively segment the brain tumor from the surrounding tissue. This high accuracy is indicative of the model's ability to effectively delineate the boundaries of brain tumors and separate them from the surrounding healthy tissue. After the segmentation step, the segmented images were used as input for the 3D CNN classifier, which was trained to classify the brain tumor into its respective type. The classification performance was evaluated using accuracy, and a value of accuracy 96% was obtained. This result demonstrates the ability of the 3D CNN to accurately classify the brain tumor based on the segmented images. Overall, the results of this research show that the use of 3D U-Net for segmentation and 3D CNN for classification, in combination, can achieve high accuracy in detecting and identifying brain tumors in medical images. The whole integration of these state-of-the-art techniques not only improves the efficiency of diagnosis but also enhances the precision and reliability of brain tumor identification. Moreover, the high accuracies achieved by the 3D U-Net and 3D CNN impart confidence in the clinical applicability of this approach, as it has the potential to significantly aid healthcare professionals in making informed decisions for patients.

Additionally to its high accuracy, the proposed deep learning approach demonstrate other remarkable qualities that make it an necessary tool in clinical practice. Its ability to automatically segment brain tumors from medical images significantly reduces the burden on radiologists and clinicians, allowing them to focus on critical decision-making rather than laborious manual segmentation tasks. Furthermore, the model's potential for real-time application, once optimized for faster inference times, could lead to swift and efficient diagnosis, ultimately translating into improved patient care and outcomes.

To ensure the reliability and robustness of the proposed approach, a comprehensive evaluation was carried out, including comparisons with other state-of-the-art models from the literature. The achieved segmentation accuracy of 98% outperforms previous works, such as the 2D-Unit model for brain tumor segmentation and classification purposes, which reported a segmentation accuracy of 93%. Similarly, the classification accuracy of 96% for the proposed model surpasses the accuracy of the 3D U-net model, which stood at 90%. These comparisons demonstrate the superior performance and potential of the proposed approach, underscoring its significance in advancing the field of brain tumor analysis.

By combined power of the 3D U-Net for segmentation and the 3D CNN for classification has helped in a new era in medical imaging analysis, significantly enhancing the accuracy and efficiency of brain tumor detection and identification. The outstanding results achieved in this research hold huge potential for transforming clinical practice and positively impacting patient outcomes. By providing clinicians with a reliable and automated tool for brain tumor analysis, this approach paves the way for more accurate and timely diagnosis, leading to improved treatment planning and ultimately, better patient care.

## 4.6 Summary

The primary focus of this study to develop a robust and accurate deep learning approach for the detection and identification of brain tumors in medical images. The proposed methodology involved the utilization of two advanced techniques: the 3D U-Net model for segmentation and the 3D CNN model for classification. During the segmentation phase, the 3D U-Net model demonstration excellent performance, achieving an impressive accuracy rate of 98% in precisely isolating brain tumors from the surrounding tissue. This level of accuracy is crucial in ensuring precise and reliable localization of tumors, which forms the foundation for subsequent analyses. In the subsequent classification phase, the 3D CNN model further solidified the approach's efficacy by accurately categorizing brain tumor types with a remarkable accuracy of 96%. This accurate classification holds immense potential in aiding healthcare professionals in making informed decisions about the most appropriate treatment strategies based on the tumor's specific characteristics. The cumulative findings of this research highlight the immense potential of the proposed deep learning approach in significantly improving brain tumor diagnosis and treatment. By achieving high accuracies in both segmentation and classification tasks, the proposed method lays a strong foundation for future advancements in medical imaging analysis.

The 3D U-Net model's proficiency in precisely segmenting brain tumors, in conjunction with the accurate classification achieved by the 3D CNN model, ensures a comprehensive and reliable brain tumor analysis. Such a combination of techniques holds great promise for optimizing clinical decision-making, ultimately leading to improved patient care and outcomes.

# CHAPTER 5

# CONCLUSION

In this study, deep learning approaches for classifying and segmenting brain tumors are implemented. Brats 2019 datasets are used. Brat's 2019 datasets consist of 335 patient reports involving 76 LGG(low-grade-gliomas) and 259 HGG (high-grade gliomas) patients. Each MRI images consist of four T1-weighted sequences (T1), T2-weighted (T2), FLAIR, and T1 with gadolinium-enhanced contrast (T1c). Deep learning 3D U-net architecture is used for the segmentation of brain tumors and classification purposes, implemented 3D CNN. The research goal is to analyze the performance of 3D U-net and 3D CNN to increase the accuracy of segmentation and classification. Throughout the project, python 3.7 is used as the development language. Tensor flow Keras library used to build 3D U-Net model and 3D CNN model. To improve the performance of the two models, separately studied the parameters of the two models. Completely explained different activation functions in 3D U-net and 3D CNN, the effect of loss function selection of different pooling methods, the optimizer used, different convolution layers, pooling layers, and fully connected layers. Before training, the data preprocessing method is used.

Firstly perform pre-processing steps on the images to reduce the dimensionality of the input images before feeding them to other network. By evaluate the performance of the network in segmentation and then classify HGG and LGG tumors and also present the results in terms of accuracy. After data preparation, the next step is to train the model. Both HGG and LGG datasets are trained through models for segmentation and classification. After segmentation, collected all segmented images and then performed classification on the segmented images.

The segmentation accuracy of the model is 98% and the overall classification accuracy of the model is 96%. The result shows that the 3D U-Net and 3D CNN model achieves state-of-the-art results in both accuracy and loss when compared to the other existing methods for brain tumor segmentation and classification.

One of the critical challenges in brain tumor analysis is the precise delineation of tumor boundaries, especially for irregular and complex tumors. The future aim to explore advanced segmentation techniques, such as multi-task learning and attention mechanisms, to improve the model's ability to accurately identify tumor boundaries. Achieving precise tumor segmentation is essential for optimizing treatment planning and reducing the risk of damaging healthy surrounding tissues during surgery or radiation therapy.

Additionally, incorporating data from longitudinal studies and follow-up scans could enable the model to track tumor progression and assess treatment response over time. Longitudinal analysis of brain tumor images can provide valuable insights into tumor growth patterns and treatment efficacy, ultimately contributing to improved patient management and care.

In conclusion, this study marks a significant advancement in the field of medical imaging analysis, particularly in brain tumor detection and identification. The implementation of deep learning approaches, namely the 3D U-Net and 3D CNN models, has demonstrated exceptional accuracy and performance in segmentation and classification tasks. The success of this research sets the stage for future advancements in medical image analysis and has the potential to transform clinical practice by providing clinicians with a powerful and automated tool for brain tumor diagnosis and treatment planning.

In the Future, the model will train with additional clinical data or genetic data. Will train the model on other medical image modalities such as CT or PET to allow for multi-model analysis and potentially improve the accuracy of the results. To remove the tumor without harming the nearby healthy tissues, must identify the precise irregular and complicated borders of the affected areas.

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