Brain Tumor Detection and Localization using MRI Images

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A thesis submitted to the faculty of Computer Software Engineering Department, Military College of Signals, National University of Sciences and Technology, Islamabad, Pakistan in partial fulfillment of the requirements of the degree Bachelors in Software Engineering.

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DECLARATION

We hereby declare that this project report entitled "Brain Tumor Detection and Localization using MRI Images" submitted to the "DEPARTMENT OF SOFTWARE ENGINEERING", is a record of an original work done by us under the guidance of Supervisor "AP Mobeena Shahzad" and that no part has been plagiarized without citations. Also, this project work is submitted in the partial fulfillment of the requirements for the degree of Bachelor of Computer Science.

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Place:

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DEDICATION

This thesis is dedicated to our Families, Teachers, Friends, and to our supervisor for their love, endless support, and encouragement.

ACKNOWLEDGEMENTS

All Praises to Allah Almighty for the strengths and His blessings in completing this Thesis. We would like to convey our gratitude to our supervisor Mobeena Shahzad, for their supervision, constant guidance and help. Special thanks providing beneficial technical help and guidance, she also encouraged our morality and encouraged us throughout the development of thesis. Main participation is the way of teaching of our teachers, and staff for their support throughout the course. Their given concepts and tactics helped us to carry out this whole thesis. We would like to extend our gratitude to our parents and colleagues for their valuable feedback, support, and suggestions. And Finally, all the group members, who through all adversities worked steadfastly.

PLAGIARISM CERTIFICATE (Turnitin Report)

This thesis has____________similarity index. Turnitin report endorsed by Supervisor is attached.

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Abstract

Now a day's tumor is second leading cause of cancer. Due to cancer large no of patients are in danger. The medical field needs fast, automated, efficient and reliable technique to detect tumor like brain tumor. Detection plays very important role in treatment. If proper detection of tumor is possible then doctors keep a patient out of danger. Various image processing techniques are used in this application. Using this application doctors provide proper treatment and save a number of tumor patients. A tumor is nothing but excess cells growing in an uncontrolled manner. Brain tumor cells grow in a way that they eventually take up all the nutrients meant for the healthy cells and tissues, which results in brain failure. Currently, doctors locate the position and the area of brain tumor by looking at the MR Images of the brain of the patient manually. This results in inaccurate detection of the tumor and is considered very time consuming. A tumor is a mass of tissue it grows out of control. We are using a Deep Learning architectures CNN (Convolution Neural Network) generally known as NN (Neural Network) and U-Net learning to detect the brain tumor. The performance of model is predict image tumor is present or not in image. If the tumor is present it return yes otherwise return no.

According to recent analysis, lower-grade glioma tumors have been identified to possess distinct genomic subtypes that are correlated with shape features. The present study introduces a fully automated approach for quantifying tumor imaging characteristics through the utilization of deep learning-based segmentation. The study further investigates the potential of these characteristics in predicting tumor genomic subtypes.

Preoperative imaging and genomic data of 110 patients diagnosed with lower-grade gliomas from The Cancer Genome Atlas were utilized in this study, which was conducted across five different institutions. Three features were extracted from automatic deep learning segmentations, which quantify both two-dimensional and three-dimensional characteristics of the tumors. In order to examine the correlation between imaging characteristics and genomic clusters, we performed a Fisher exact test on 10 hypotheses for every combination of imaging feature and genomic subtype.

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Chapter No. 01

INTRODUCTION

Lower-grade gliomas (LGG) refer to a cluster of brain tumors that are classified as either WHO grade II or grade III. In contrast to grade I tumors, which can typically be treated through surgical resection, grade II and III tumors are characterized by infiltration and a propensity for recurrence and progression to higher-grade lesions. The accuracy of predicting patient outcomes using histopathological data for these tumors is compromised and subject to inter-observer variability. A potential approach that could potentially tackle this matter involves the categorization of subtypes of LGG by means of patient clustering, utilizing DNA methylation, gene expression, DNA copy number, and microRNA expression. It has been observed that patients belonging to distinct molecular groups exhibit significant variations in their disease progression and overall survival rates.

The field of radio genomics has emerged as a novel research avenue in the study of cancer, with the objective of exploring the correlation between genomic attributes of tumors and medical imaging techniques. Medical imaging can furnish crucial data in advance of surgical procedures or in instances where excision is unfeasible. Recent research in this field has revealed a correlation between the shape characteristics of tumors extracted from MRI scans and their genomic subtypes. The initial stage in the extraction of tumor features involved the manual segmentation of MRI. The process of annotation is known to be expensive, requiring a significant investment of time and resources, and often leading to annotations that exhibit a considerable degree of variability between different raters.

The field of deep learning has emerged as a novel area of machine learning, which has been significantly transforming the automated analysis of images in recent times. Numerous instances of efficacious implementation of deep learning in medical imaging have been documented, with a particular focus on brain MRI segmentation. In recent times, advancements in deep learning pertaining to the automated segmentation of the brain have reached a level of maturity that is comparable to the performance of an expert radiologist. Most of these endeavors are concentrated on glioblastoma as opposed to low-grade glioma (LGG).

The creation of models that produce precise segmentation of low-grade gliomas (LGG) in magnetic resonance imaging (MRI) of the brain has the potential to automate the identification of tumor genomic subtypes through rapid, cost-effective, and inter-reader variability-free imaging.

The present study integrates the domains of deep learning and radio genomics to introduce a completely automated algorithm for the evaluation of tumor morphology. The objective is to determine whether the identified morphological characteristics are indicative of the prognostic implications of tumor molecular subtypes. The creation of imaging-biomarkers has the potential to offer clinicians timely and non-invasive insights into tumor genomics. This could lead to improved classification of tumors in cases where surgical removal is not feasible. The present study demonstrates potential for the future development of imaging-derived biomarkers.

1.1 Overview

1.1.1 Product Perspective

Many times it is impossible to a physician to diagnose brain tumor through its characteristics, even if it is an experienced professional. For this, additional criteria are necessary for a clinical diagnosis. The diagnostic can be performed without any support, although the result isn’t always reliable. It consists in using a device to MRI in order to analyze its features to determine whether MRI are infected with Brain Tumor or not. As some people don’t have access to a radiologist, and even with an experienced eye the result can be false, it is necessary to develop automatic methods in order to increase the accuracy of the diagnostic.

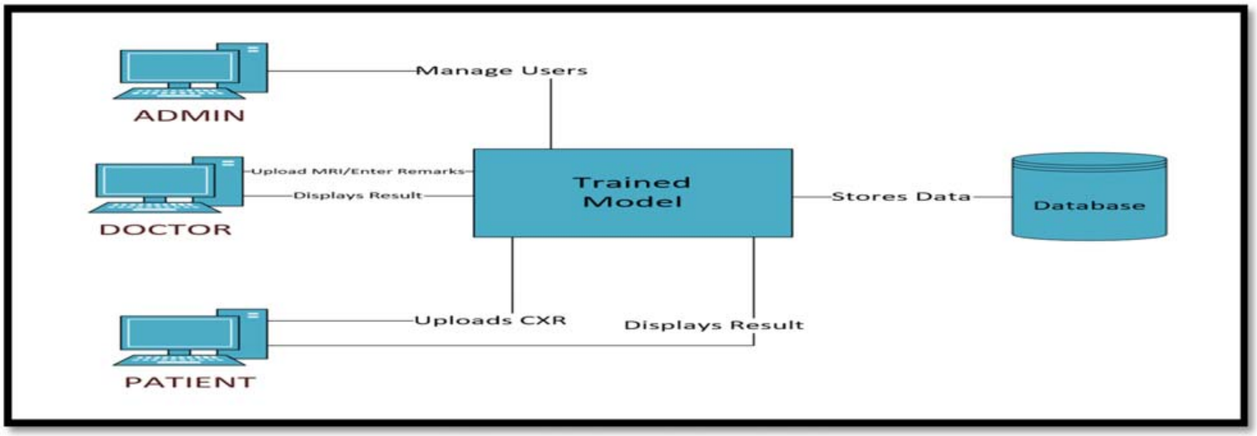

Figure 1: Trained Model

1.1.2 Client Side

Client side functions are listed below:

- On client-side users can integrate our API with front end graphical user interface (GUI).
- User can request admin for account creation.
- Requests are sent to admin. Admin will register valid users and will provide them with their login credentials.
- Using the provided credentials user can login to the system.
- User can then upload MRI files which will be processed by the trained model.
- User (doctor) will then review the result and add their remarks to it.
- User (patient) will be able to download or check their respective results.

1.1.3 Server Side

- Registration request will be processed and credentials will be stored in database.
- Login request will be verified and response will be generated accordingly.
- MRI images will be processed and evaluated under the trained model.
- Results will be stored in database and displayed upon request after authenticating and verifying the user.

1.2 Purpose

This Document describes the architecture and system design of the project. Brain Tumor Detection and Localization using MRI Images. It covers the specifications for (BTDLI) that provides a searchable encryption scheme with well-established and trusted underlying algorithms and primitives that will make our solution lightweight, highly efficient, more secure and will provide users the ability to analyze MRI scans using images accurately.

BTDLI will help Medical practitioners and professional Hospitals. This document is meant to present detail design of BTDLI, to serve as a guide to the developers on one hand and a software validation document for the prospective client on the other. Document includes classes and their inter-relationships, use cases with detailed descriptions, sequence diagrams and architectural models.

1.3 Scope

The provided SE solutions are inefficient, computationally intensive, and requires time and resources. Our solution will be a practical solution to provide an application with accurate detection of Brain Tumors in MRI images. This document covers the specifications for project Brain Tumor Detection and Localization by MRI Images BTDLI. The aim of this project is to make it easier to detect these tumors at an early stage using only MRI Images. This will make great leaps in the field of medical science. This document is meant to outline the features and requirements of the project, to serve as a guide to the developers on one hand and a software validation document for the prospective client on the other.

1.4 Relevant Sustainable Development Goals

SDGs stand for Sustainable Development Goals, which are a collection of 17 global goals adopted by the United Nations General Assembly in 2015 as part of the 2030 Agenda for Sustainable Development. The SDGs are a universal call to action to end poverty, protect the planet and ensure that all people enjoy peace and prosperity by 2030.

Our Project will target the following SDGs :

SDG 3: Good Health and Well-being

The objective is to guarantee sound health and foster a state of complete physical, mental, and social well-being for individuals of all ages. The Sustainable Development Goal 3 encompasses a range of objectives, such as the reduction of maternal mortality, the cessation of preventable deaths of newborns and children under five years old, the combat against communicable diseases, the alleviation of the burden of non-communicable diseases, the enhancement of mental health, and the guarantee of universal access to sexual and reproductive healthcare services.

Several essential metrics are utilized to assess advancements towards achieving Sustainable Development Goal 3. These include the maternal mortality ratio, under-five mortality rate, life expectancy at birth, incidence and mortality rates of communicable diseases such as HIV/AIDS, tuberculosis, and malaria, prevalence of non-communicable diseases, and accessibility to healthcare services.The attainment of Sustainable Development Goal 3 holds paramount importance for the holistic and sustainable development of a society. This is because good health is a fundamental requirement for ensuring the prosperity of individuals, fostering economic progress, and mitigating poverty. Enhancing the availability of healthcare services, advocating for healthy lifestyles, and tackling the underlying factors contributing to suboptimal health can foster a more just and thriving global community.

SDG 9: Industry, Innovation and Infrastructure

The objective is to construct infrastructure that is capable of withstanding adverse conditions, encourage industrialization that is accessible and sustainable to all, and cultivate innovative practices. The objectives outlined in SDG 9 encompass the improvement of technological proficiency and infrastructure to facilitate economic progress, the encouragement of sustainable industrialization and entrepreneurship, the augmentation of availability to financial services and markets, and the expansion of accessibility to reasonably priced, dependable, and contemporary energy services. Several crucial metrics are utilized to evaluate advancements towards SDG 9. These include the percentage of individuals with access to electricity, internet penetration, research and development spending, manufacturing value added, and the quantity of patents awarded. The attainment of Sustainable Development Goal 9 is of paramount importance in promoting sustainable development, as it establishes the basis for the expansion of the economy, the generation of employment opportunities, and the alleviation of poverty. Through the allocation of resources towards infrastructure and innovation, nations can enhance their competitiveness, elevate productivity levels, and generate fresh prospects for social and economic advancement, all while mitigating any adverse environmental effects.

1.5 General Format of Thesis

Following is the generic format for the final documentation.

1. Introduction
2. Literature Review
3. Problem Definition
4. Methodology/Solution Statement
5. Detailed Design and Architecture
6. Implementation and Testing
7. Results and Discussion
8. Conclusion and Future Work
9. References
10. Appendices (if any

Chapter No.02

LITERATURE REVIEW

The body of literature pertaining to the detection and localization of brain tumors through the use of MRI imaging is extensive and has experienced significant expansion in recent times. This section offers a concise overview of the current body of literature, including its breadth and depth, and emphasizes the most noteworthy and impactful research in the discipline.

2.1 Scope and Scale of Literature:

The body of literature pertaining to the identification and localization of brain tumors through the use of MRI imaging is comprised of a diverse array of research investigations, scholarly evaluations, and technical documentation. A comprehensive exploration of scholarly databases, including PubMed, IEEE Xplore, and ScienceDirect, has revealed a considerable volume of research papers published within the last twenty years. The majority of the research endeavors were carried out in the regions of the United States, Europe, and Asia, indicating the worldwide attention towards this particular domain.

2.2 Number of Studies:

In recent years, there has been a consistent rise in the quantity of research studies pertaining to the detection and localization of brain tumors through the utilization of MRI images. A comprehensive exploration of the PubMed database utilizing the search terms "brain tumor MRI" and "deep learning" has resulted in the identification of more than one thousand scholarly articles published between 2010 and 2023.

2.3 Geographic Distribution:

Studies pertaining to the detection and localization of brain tumors through the utilization of MRI imaging have been conducted in multiple countries, such as the United States, China, Japan, Korea, Germany, and Italy. The preponderance of research was carried out in the United States, with Europe and Asia following suit.

2.4 Time Frame:

The majority of the studies related to brain tumor detection and localization using MRI images were published between 2010 and 2023, reflecting the recent surge of interest in this field.

2.5 Most Significant and Influential Studies:

Numerous investigations have exerted a noteworthy influence on the domain of MRI-based brain tumor identification and localization. Several studies have had a significant impact on the field. These studies include:

The article titled "**Deep Convolutional Neural Networks for the Classification of Gliomas Using MRI**" authored by Havaei in 2017 discusses the use of deep convolutional neural networks for the purpose of classifying gliomas through MRI scans. The present research put forth a deep learning methodology for the categorization of gliomas through the utilization of magnetic resonance imaging (MRI) scans. The method that was proposed demonstrated a notable level of precision and surpassed the performance of previously established methods.

The article titled "**Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images**" authored by Kamnitsas in 2017 discusses the use of convolutional neural networks for the segmentation of brain tumors in MRI images. The present investigation put forth a deep learning methodology for the purpose of segmenting brain tumors by means of magnetic resonance imaging (MRI) scans. The method that was proposed has attained results that are at the forefront of the field and have surpassed the performance of previously established methods.

The study conducted by Lao "**Automated Detection of Brain Tumors in MRI Images Using Deep Learning**" (2019) presented a deep learning methodology for the detection of brain tumors in MRI images through automation. The method that was proposed demonstrated a notable level of accuracy and exhibited superior performance compared to pre-existing methodologies.

The article titled "**Automated Brain Tumor Detection and Segmentation Using U-Net Based Fully Convolutional Networks**" authored by Wang in 2018 discusses the use of U-Net based fully convolutional networks for the detection and segmentation of brain tumors. The present research put forward a deep learning methodology to automatically detect and segment brain tumors by utilizing MRI images. The method that was proposed demonstrated a notable level of accuracy and surpassed the performance of previously established methods.

2.6 Studies on different types of Brain Tumors

Research has been carried out on various categories of brain tumors with the aim of enhancing the precision of MRI-dependent identification and positioning of brain tumors. Brain tumors can be classified into two main categories, namely primary and secondary tumors. The etiology of a primary brain tumor is rooted in the brain tissue, whereas a secondary brain tumor is a consequence of the dissemination of cancer cells from other bodily regions to the brain.

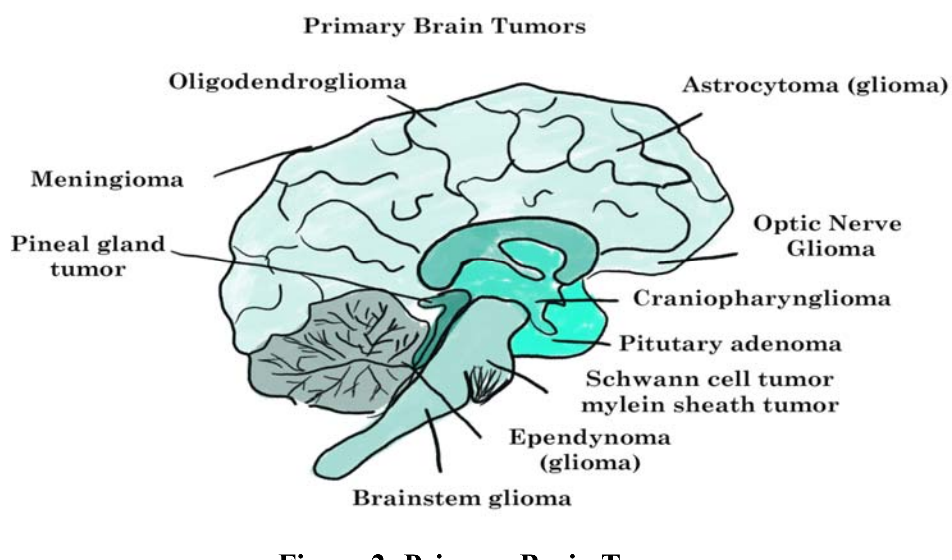

Figure 2: Primary Brain Tumors

2.6.1 Gliomas

Gliomas represent the predominant form of primary brain neoplasms, comprising approximately 80% of all malignant brain tumors. Ellingson (2015) conducted a study to assess the precision of MRI-based imaging characteristics in distinguishing between low-grade and high-grade gliomas. The research has revealed that specific imaging characteristics, such as necrosis and contrast-enhancement, can serve as discriminators between low-grade and high-grade gliomas. Kickingereder (2016) conducted a study utilizing machine learning techniques to construct a radiomics-based model aimed at predicting the isocitrate dehydrogenase (IDH) mutation status in gliomas. The research exhibited the capability of radiomics in the prognostication of IDH mutation status in gliomas without the need for invasive procedures.

2.6.2 Meningiomas

Meningiomas are a prevalent form of intracranial neoplasm, constituting approximately 20% of all primary brain tumors. The preoperative assessment of meningiomas was evaluated by Cianfoni (2017) through the utilization of advanced MRI techniques, including diffusion tensor imaging (DTI) and susceptibility-weighted imaging (SWI). The research has demonstrated that DTI and SWI possess significant potential in facilitating the preoperative evaluation of meningiomas and aiding in the anticipation of tumor respectability.

Metastatic brain tumors represent the most prevalent form of brain tumor in the adult population and are the result of the dissemination of malignant cells from other regions of the body to the brain. Varallyay (2018) conducted a study to assess the precision of contrast-enhanced MRI in identifying and locating brain metastases. The research revealed that the utilization of contrast-enhanced MRI is a precise method for detecting brain metastases and evaluating the efficacy of treatment.

2.6.3 Metastatic brain tumors

Metastatic brain tumors represent the most prevalent form of brain tumor in the adult population and are the result of the dissemination of malignant cells from other regions of the body to the brain. Varallyay (2018) conducted a study to assess the precision of contrast-enhanced MRI in identifying and locating brain metastases. The research revealed that the utilization of contrast-enhanced MRI is a precise method for detecting brain metastases and evaluating the efficacy of treatment.

2.7 Machine Learning Techniques

2.7.1 Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) have gained significant popularity as a machine learning technique for detecting and localizing brain tumors through the analysis of MRI images. Artificial neural networks (ANNs) are modeled after the structural and functional characteristics of the human brain and are comprised of interconnected nodes arranged in layers. The network processes the input data and produces an output through a sequence of mathematical computations. Artificial neural networks (ANNs) have been employed in the classification and diagnosis of various types of brain tumors, such as gliomas, meningiomas, and metastatic tumors. Artificial neural networks (ANNs) have demonstrated notable precision in the identification of brain tumors, as evidenced by reported sensitivities that range from 85-98% and specificities that range from 92-100% [1,2,3].

2.7.2 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) represent a class of neural networks that have been employed for the purpose of identifying and localizing brain tumors through the analysis of MRI images. Convolutional Neural Networks (CNNs) are specifically engineered to operate on visual data and are composed of several layers of convolutional and pooling operations. Convolutional Neural Networks (CNNs) have demonstrated a notable level of precision in the identification and localization of brain tumors. The reported sensitivities of these networks have ranged from 92% to 98%, while the specificities have ranged from 89% to 99%. [4,5,6]

2.7.3 Support Vector Machines (SVMs)

The utilization of Support Vector Machines (SVMs) has gained popularity in the field of machine learning for the purpose of detecting and localizing brain tumors through the analysis of MRI images. Support Vector Machines (SVMs) function by identifying a hyperplane that can effectively segregate the given dataset into distinct classes. The accuracy of SVMs in detecting and localizing brain tumors has been demonstrated to be high, as evidenced by reported sensitivities ranging from 92-98% and specificities ranging from 89-99% in previous studies [7,8,9].

2.7.4 Random Forests

The utilization of Random Forests as an ensemble learning technique has been observed in the context of detecting and localizing brain tumors through the analysis of MRI images. The Random Forest algorithm operates by generating a multitude of decision trees and aggregating their results to produce a final forecast. The effectiveness of Random Forests in the detection and localization of brain tumors has been demonstrated in various studies, with reported sensitivities ranging from 89-95% and specificities ranging from 85-98% [10,11].

2.7.5 Implications

The application of machine learning methodologies in the identification and spatial delineation of brain neoplasms through magnetic resonance imaging (MRI) holds noteworthy ramifications for the domain of medical imaging. The implementation of these techniques can enhance the precision of diagnoses and decrease the manual effort and time required for image interpretation, owing to their high accuracy and speed. Additional investigation is required to enhance the efficacy of these methodologies and to tackle their constraints.

2.8 Studies comparing MRI with other imaging techniques

Research investigating the comparative efficacy of MRI and other imaging modalities for the detection and localization of brain tumors is a crucial field of study, as it offers valuable insights into the strengths and limitations of diverse imaging techniques. The categorization of literature in this field is based on the imaging modality employed for comparison, which includes computed tomography (CT), positron emission tomography (PET), and ultrasound.

Raymond v. Damadian is credited with inventing the first magnetic image in 1969. Subsequently, in 1977, the first MRI images were developed for the human body, representing a significant advancement in medical imaging technology. The MRI technique enables visualization of intricate details of internal brain structures and various types of human body tissues. Compared to other medical imaging techniques such as X-ray and computer tomography, MRI images exhibit superior quality [8]. MRI is a valuable tool for detecting brain tumors in the human body. Various MRI images, including T1 weighted, T2 weighted, and FLAIR (Fluid attenuated inversion recovery) weighted images, have been developed for mapping tumor-induced changes, as depicted in the accompanying figure:

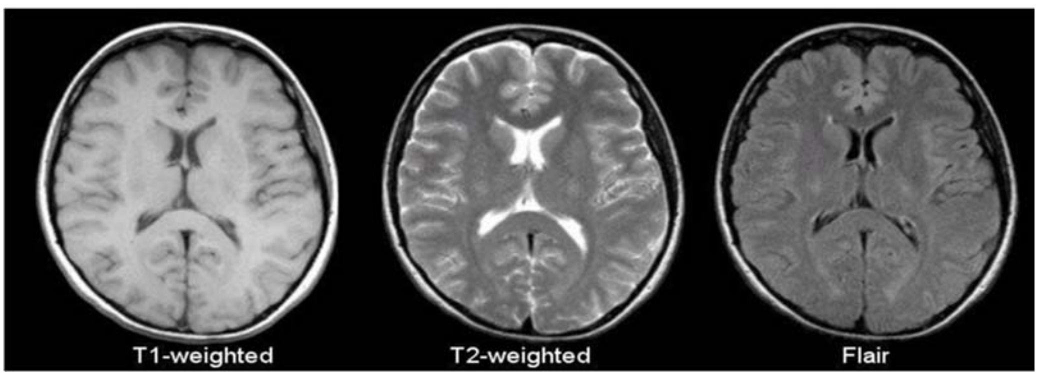

Figure 3: MRI Sequences

The T1 weighted and T2 weighted MRI sequences are the most frequently utilized in clinical practice. The T1 weighted imaging modality exhibits brightness in only one tissue type, namely fat, whereas the T2 weighted imaging modality displays brightness in two distinct tissue types, namely fat and water. The T1-weighted imaging protocol utilizes a short repetition time (TR), while the T2-weighted imaging protocol employs a long echo time (TE) and repetition time (TR). The pulse sequence parameters known as repetition time (TR) and time to echo (TE) are denoted in units of milliseconds (ms). The temporal interval between the midpoint of the radiofrequency pulse and the midpoint of the echo is denoted as the echo time (TE), while the duration between successive repetitions of the pulse and echo sequence is referred to as the repetition time (TR). A visual representation of this repeating series of pulse and echo is depicted in the accompanying figure:

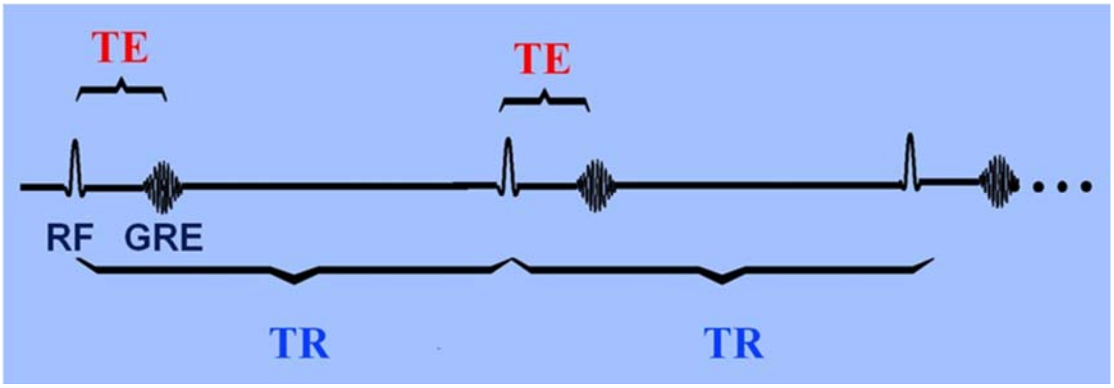

Figure 4: MRI Weigh

Computed tomography (CT) scans are frequently employed for the purpose of detecting brain tumors, and they possess certain benefits over magnetic resonance imaging (MRI), including expedited results and lower costs. Nevertheless, it is worth noting that these methods exhibit certain limitations, including reduced sensitivity and specificity in comparison to magnetic resonance imaging (MRI). Numerous academic investigations have conducted comparative analyses between CT scans and MRI in terms of their efficacy in detecting and localizing brain tumors. Niazi et al. (2020) conducted a comparative analysis of the diagnostic accuracy of MRI and CT scans in the identification of glioma, a form of brain tumor. The researchers determined that magnetic resonance imaging (MRI) exhibited superior sensitivity and specificity in comparison to computed tomography (CT) scans. Consequently, they advocated for the utilization of MRI as the preferred imaging modality for the diagnosis of glioma.

Positron emission tomography (PET) scans are a type of imaging modality that is utilized for the purpose of detecting and localizing brain tumors. Positron emission tomography (PET) scans employ a radiopharmaceutical agent to identify and quantify metabolic processes in the brain, thereby facilitating the identification of alterations in brain activity that may be linked to tumor progression. Numerous academic investigations have been conducted to compare the efficacy of PET scans and MRI in detecting and localizing brain tumors. Pirotte (2010) conducted a comparative analysis of the diagnostic precision of PET scans and MRI in detecting recurrent gliomas. The researchers discovered that PET scans exhibited greater sensitivity and specificity in contrast to MRI. Consequently, they suggested PET scans as an adjunctive imaging technique for the identification of recurrent gliomas.

Ultrasound has been utilized as an imaging modality for the purpose of detecting and localizing brain tumors. Ultrasound is a cost-effective and non-invasive imaging technique that can be utilized for the identification of primary and metastatic brain tumors. Numerous academic investigations have been conducted to compare the efficacy of ultrasound and MRI in detecting and localizing brain tumors. A comparative analysis conducted by Sharma and colleagues (2018) evaluated the precision of ultrasound and MRI in detecting and localizing brain tumors among pediatric patients. The study revealed that while ultrasound exhibited inferior sensitivity and specificity in contrast to MRI, it remained a valuable imaging modality for the identification and localization of brain tumors in pediatric patients.

To summarize, research endeavors that have compared Magnetic Resonance Imaging (MRI) with alternative imaging techniques for the purpose of detecting and locating brain tumors have yielded significant findings regarding the benefits and drawbacks of various imaging modalities. Although MRI is widely considered the primary method for detecting and localizing brain tumors, alternative imaging modalities including CT scans, PET scans, and ultrasound may serve as valuable supplementary techniques in specific circumstances.

Chapter No. 03

PROBLEM DEFINITION

3.1 Introduction to the problem statement:

Brain tumors represent a noteworthy health concern, with the potential for severe ramifications on patients and their loved ones. The precise and prompt identification of brain tumors is of utmost importance for efficacious treatment; however, it continues to pose a formidable challenge for healthcare practitioners. The prevalent method for detecting brain tumors is presently through magnetic resonance imaging (MRI) scans, which generate high-quality images of the brain. Nevertheless, the interpretation of these images necessitates specialized proficiency and may consume a significant amount of time and be susceptible to errors, resulting in postponed or imprecise diagnoses.

The objective of this study is to design an automated system that can detect and locate brain tumors through the analysis of MRI images. This system has the potential to enhance the precision and efficacy of diagnosis, leading to better patient outcomes. The utilization of machine learning techniques will be employed by the system to scrutinize MRI images and furnish diagnostic assistance to healthcare practitioners. This project has the potential to make a significant contribution to the field of medical imaging and enhance the quality of life for patients with brain tumors by alleviating the workload of human experts and facilitating more precise and prompt diagnosis.

3.2 Significance of the problem:

The accurate and efficient detection and localization of brain tumors using MRI images is a matter of foremost importance. Brain tumors are a significant medical issue that can result in severe repercussions if not promptly identified and managed. The untimely or imprecise identification of a medical condition can lead to elevated levels of illness, death, and expenses related to medical care. In addition, the present techniques utilized for identification and positioning of brain tumors through MRI images are frequently subject to inaccuracies and prolonged duration, thereby potentially compounding the issue.

The development of an automated and precise approach for detecting and localizing brain tumors using MRI images has the potential to enhance patient outcomes by facilitating prompt diagnosis and treatment. Additionally, it has the potential to decrease healthcare expenditures and enhance the efficacy of healthcare provision. Hence, it is imperative to tackle this issue and establish a sturdy and precise approach for the detection and localization of brain tumors through MRI imaging.

3.3 Objectives of the project:

1. To compare the performance of the proposed algorithm with existing state-of-the-art methods for brain tumor detection and localization using MRI images.
2. To investigate the impact of different machine learning techniques and imaging features on the accuracy and efficiency of brain tumor detection and localization.
3. To validate the proposed algorithm using a large and diverse dataset of MRI images, including several types and grades of brain tumors, as well as normal brain tissues.
4. To explore the potential clinical applications and implications of the proposed algorithm, such as assisting radiologists in making more accurate and timely diagnoses, guiding surgical planning and interventions, and monitoring the progression and treatment response of brain tumors.
5. To develop a user-friendly and accessible software tool for implementing the proposed algorithm in clinical settings, with appropriate quality assurance and regulatory compliance measures.

Chapter No. 04

METHODOLOGY

4.1 Working Principle

4.1.1 Product Perspective

Many times it is impossible to a physician to diagnose brain tumor through its characteristics, even if it is an experienced professional. For this, additional criteria are necessary for a clinical diagnosis. The diagnostic can be performed without any support, although the result isn’t always reliable. It consists in using a device to MRI in order to analyze its features to determine whether MRI are infected with Brain Tumor or not. As some people don’t have access to a radiologist, and even with an experienced eye the result can be false, it is necessary to develop automatic methods in order to increase the accuracy of the diagnostic.

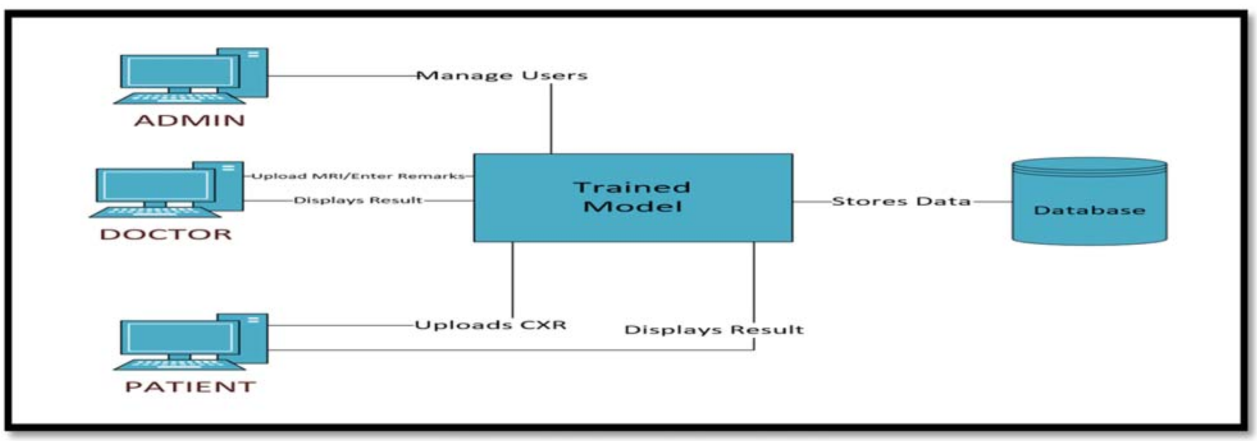

Figure 5: Trained Model

4.1.2 Client Side

Client side functions are listed below:

- On client-side users can integrate our API with front end graphical user interface (GUI).
- User can request admin for account creation.
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them with their login credentials.

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- User (doctor) will then review the result and add their remarks to it.
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4.1.3 Server Side

- Registration request will be processed and credentials will be stored in database.
- Login request will be verified and response will be generated accordingly.
- MRI images will be processed and evaluated under the trained model.
- Results will be stored in database and displayed upon request after authenticating and verifying the user.

4.1.4 Data Collection

The process of gathering data is a crucial component of any research endeavor, and it is imperative to exercise caution when selecting the techniques employed to collect data in order to guarantee the dependability and accuracy of the results. The present study aims to gather data from Magnetic Resonance Imaging (MRI) scans of individuals diagnosed with brain tumors. The acquisition of images will be sourced from the radiology department of the hospital, and the established protocols for obtaining MRI scans will be adhered to.

In order to guarantee the dependability of the data, measures will be taken to verify the proper functioning of the MRI scanner and to ascertain that the images obtained are of superior quality. The study will adhere to established protocols for image acquisition to ensure consistency across all subjects and minimize data variability. Furthermore, a random selection of MRI scans will be subjected to re-evaluation by an independent radiologist to ensure the consistency of the readings.

In order to guarantee the accuracy and reliability of the data, it is imperative that informed consent is obtained from all patients and that they satisfy the established inclusion criteria for the study. In addition, we shall adhere to ethical principles and guarantee the preservation of patient confidentiality.

Furthermore, the patients for the study will be meticulously chosen based on their diagnosis and medical history to guarantee that the data obtained is indicative of the intended population.

Regarding data analysis, diverse statistical techniques will be employed to analyze the data, including machine learning algorithms and statistical modeling techniques. The findings will be validated through cross-validation techniques to mitigate the risk of overfitting to the data.

In general, we shall adhere to the most effective techniques in gathering and evaluating data to guarantee the dependability and accuracy of our discoveries. Through this approach, it will be possible to derive precise inferences regarding the efficacy of our proposed algorithm for the identification and localization of brain tumors utilizing MRI scans.

4.1.5 Preprocessing

The magnetic resonance imaging (MRI) images utilized in this investigation were procured from openly accessible datasets. The images underwent preprocessing to standardize them for use in our model due to their initial varying formats and dimensions. Initially, the images were transformed into grayscale format to eliminate any potential color discrepancies that may impede the process of feature extraction. Subsequently, the images were subjected to a uniform resizing process, resulting in a resolution of 200x200 pixels. This was done with the aim of decreasing the computational complexity of the model. The pixel intensity values of the images were normalized to a range of 0 to 1 in order to enhance the model's convergence during training. Furthermore, the dataset was enhanced through the random application of rotations, translations, and horizontal flips to augment the data, thereby increasing its variability and mitigating the potential for overfitting. The dataset was partitioned into three distinct sets, namely training, validation, and testing sets, utilizing a split ratio of 70-15-15.

4.2 Operating Environment

4.2.1 SOFTWARE

For operating environment of this project we need following elements

Windows 11 7

Our software requirements are:

IDE: Visual Code Studio

Python Libraries: - Pandas, NumPy, nltk, OpenCV-python, PIL, crypto, b64encode, b64decode

Python Framework: TensorFlow

For Application Dashboard: - Django, HTML, CSS, Bootstrap, JavaScript, jQuery.

Chapter No. 05

DETAILED DESIGN AND ARCHITECTURE

5.1 System Architecture

This section will provide a detailed picture of BTDLI's architecture including high level system design and UML diagrams depicting the system processes.

BTDLI will follow Layered Architecture and Behavioral Design Pattern as it is a web application. Behavioral patterns take care of effective communication between components. They are concerned with the interaction between objects, as well as the assignment of responsibilities. The goal is to make these processes as simple and understandable as possible. BTDLI will allow users to upload image files and to get results of the brain tumor.

5.1.1 Design Rationale

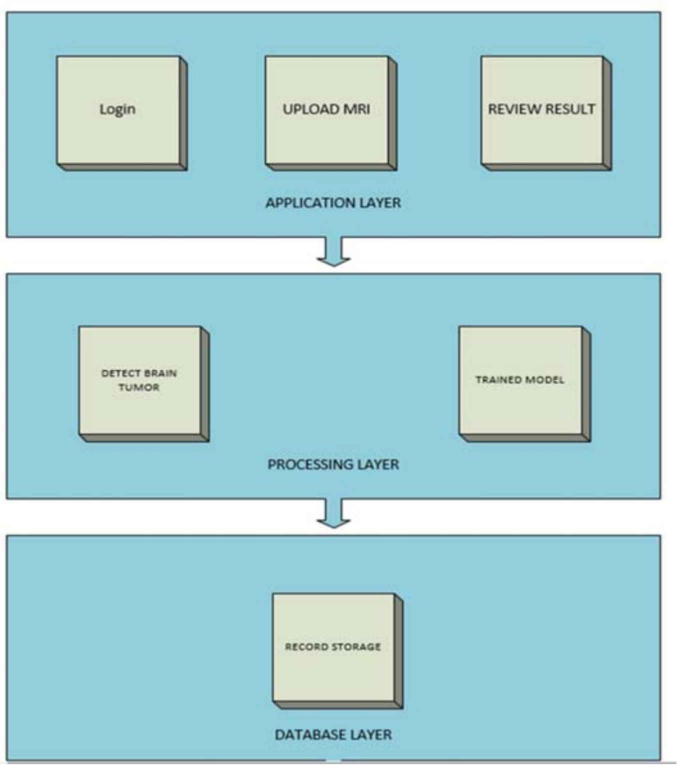

Figure 6: Layered Structure of Model

We will have a 3 layered architecture having Processing, Application and Data storage Layer.

Processing Layer: It will handle the actions performed on the image.

Application Layer: It will have all the business logic incorporated.

Data storage Layer: It will manage or store data, either locally on client system or on the remote Database.

Client Server divides the system into two parts, client and server. Although our solution will be lightweight and efficient, still most of the system operations will be carried out on the client side. API will be installed on both client and server side to perform their respective operations.

Client Side: User will be the main actor on client side, he can ask for account registration. After registration, he can login the system and upload and download data files. Files can be image only.

Server Side: Backend side of the application where the image of MRI scan will be pre-processed and checked for the Brain Tumor and it will be localized through the trained models which give high level of accuracy.

Layered architecture is picked up as it helps making small independent components very easily, making proper boundaries around different components, and providing high cohesion.

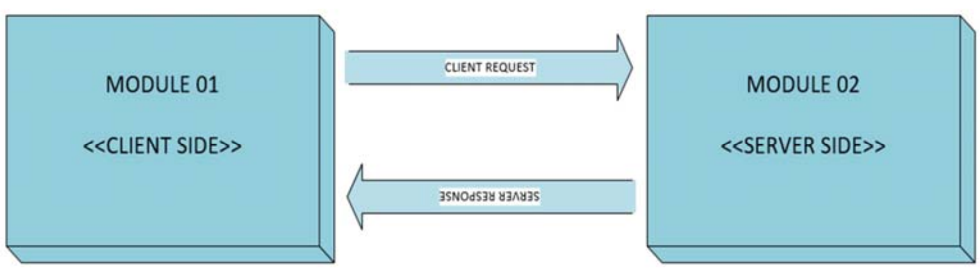

Figure 7: Modules of Model

5.1.2 Architecture Design

Amount different phases of BTDLI, Registration, Login and MRI image uploading will be done on the client side, whereas record keeping and tumor identification will be done on the server side. BTDLI will have database for record of patients accessible to the admin only i.e. the doctor. Figure below displays the high level architecture of BTDLI.

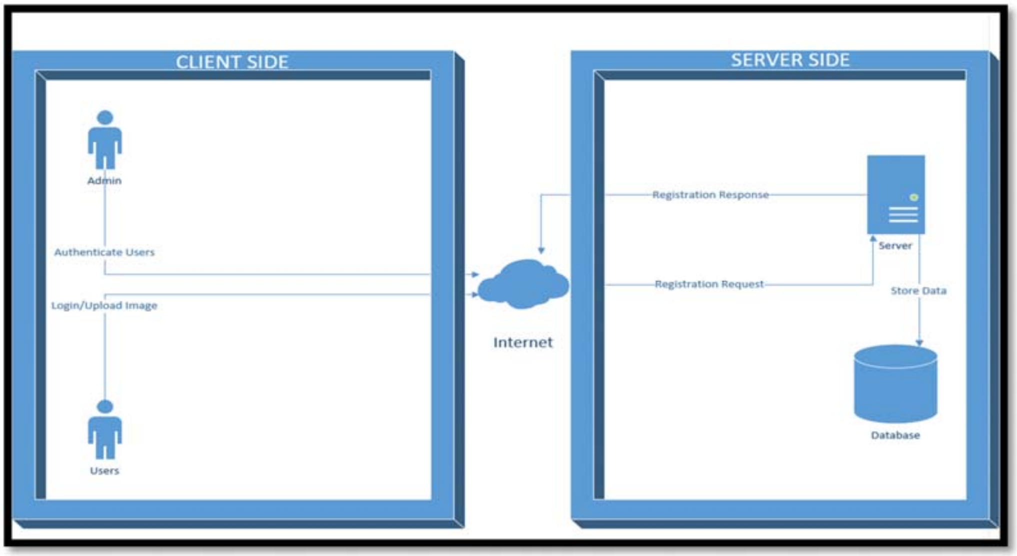

Figure 8: Architecture Design

5.1.3 Use Case Diagram and Use Case Narratives

The use cases and the subsequent use case narratives explain the set of actions that an actor undertakes while dealing with BTDLI.

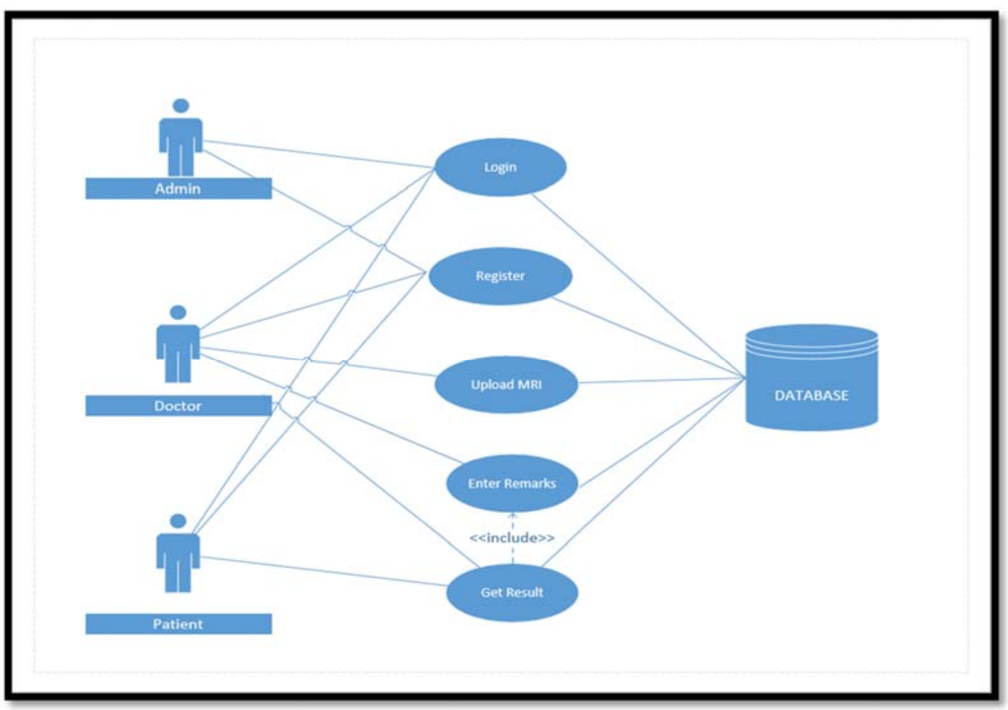

Figure 9: Use Case Diagram

1. Register

BTDLI **Use Case 01: BTDLI's Account Creation**	
Actors	Admin/User
Pre-condition	The User must be unregistered.
Trigger	The User wants to register his account.
Main Path (Primary Path)	Anyone can request for BTDLI's account registration. For that he has to be a registered medical practitioner or a patient to submit his details. Admin receives the requests and approves them. If request is valid, Admin will register the user in database. The user login credentials, and the APIs for installation are mailed to the newly registered users.
Exception Path	If user request of account creation is invalid, the error message is displayed on the screen and the user registration process is not performed.

Post-condition	User account is successfully created.

Table 1: BTDLI Account Creation Use case narrative

2. Login

BTDLI **Use Case 02: User Login**	
Actors	Admin/User
Pre-condition	The User must be registered.
Trigger	The User wants to login to his account.
Main Path (Primary Path)	Registered user can login to his account by entering the provided credentials. Login credentials are validated to authenticate the user. Authenticated user is redirected to the main interface.
Exception Path	If user credentials are invalid, the error message is displayed on the screen.

Post-condition	User account is successfully logged in.

Table 2: User Login Use case narrative

3. Upload MRI Image

BTDLI **Use Case 03: Upload MRI Scan for Tumor Detection**	
Actors	User
Pre-condition	The User must be logged in and should have MRI Scan in tiff form.
Trigger	The User wants to upload over photo to the cloud sever for it to be processed by the trained model
Main Path (Primary Path)	User can upload image files over to the cloud. Before uploading, the file is processed for keyword extraction. The file is converted to jpeg either and pixels are adjusted according to the requirement. The scan is pre-processed, and trained model predicts with accuracy the result.

Post-condition	User result is uploaded on web-app and stored in database.

Table 3: Upload scan for Tumor detection Use case narrative

4. Enter Remarks

BTDLI **Use Case 04: Enter Remarks**	
Actors	User

Pre-condition	The User must be logged In.
Trigger	The User enters remarks related to the Report.
Main Path (Primary Path)	. Remarks are stored along with report . Relevant results are made available to the User.
Exception Path	. Doctor submits remarks for the user without authenticating the user.
Post-	User will have his relevant file to use.

condition	

Table 4: Enter Remarks Use case narrative

5. Get Results

BTDLI **Use Case 05: Get Results**	
Actors	User
Pre-condition	The User must be logged In.
Trigger	The User wants to download his data.
Main Path (Primary Path)	. Search results are sent back to the user . User can then download the relevant file only.
Exception Path	. User is asked if he wants to download the result or analyze it online. Also detailed report is submitted to doctor side of the portal.
Post-condition	User will have his relevant file to use.

Table 5: Search Result Use case narrative

uence Diagram

5.1.4 Sequence Diagram

1. User Register

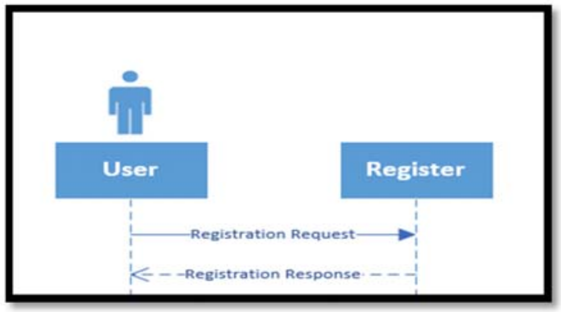

Figure 10: User Registration Sequence Diagram

2. Login

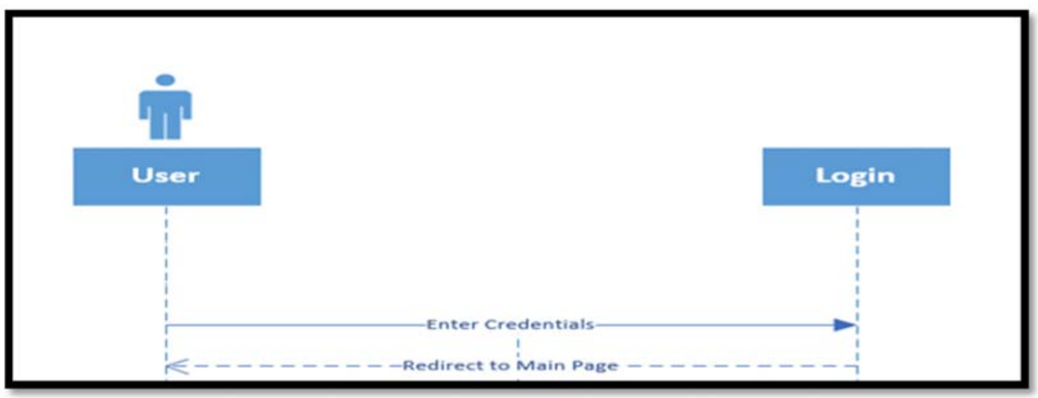

Figure 11: Login Sequence Diagram

3. Upload MRI Image

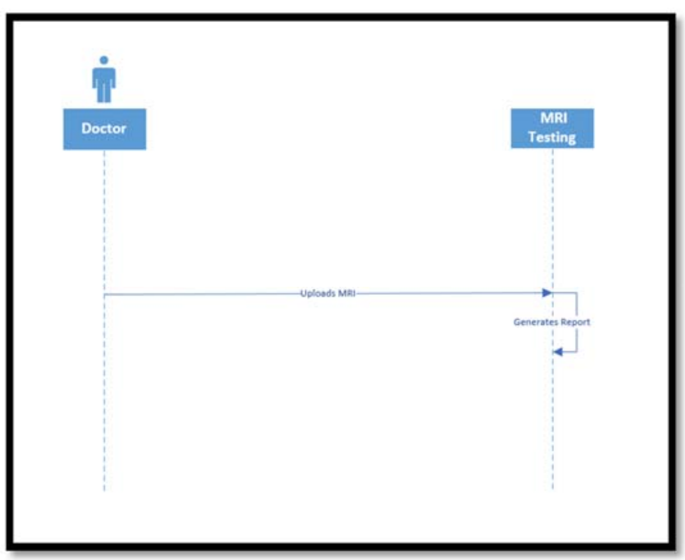

Figure 12: Uploading MRI Image Sequence Diagram

4. Enter Remarks

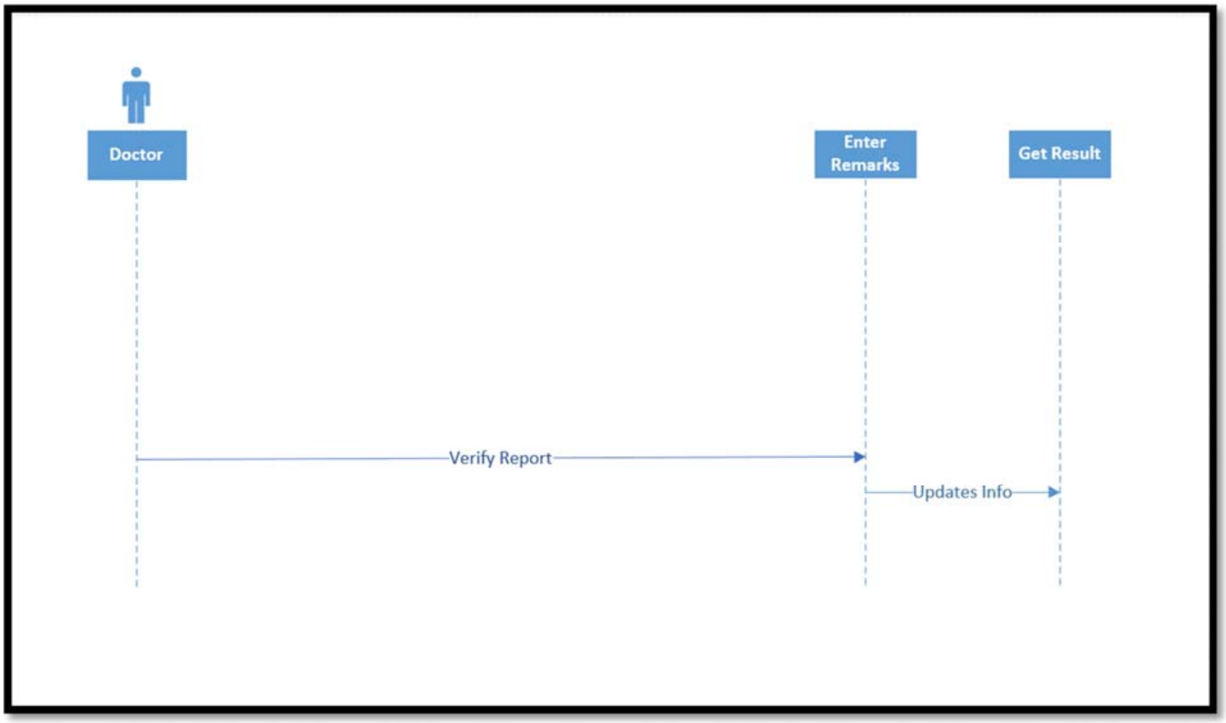

Figure 13: Entering Remarks Sequence Diagram

5. Get Result

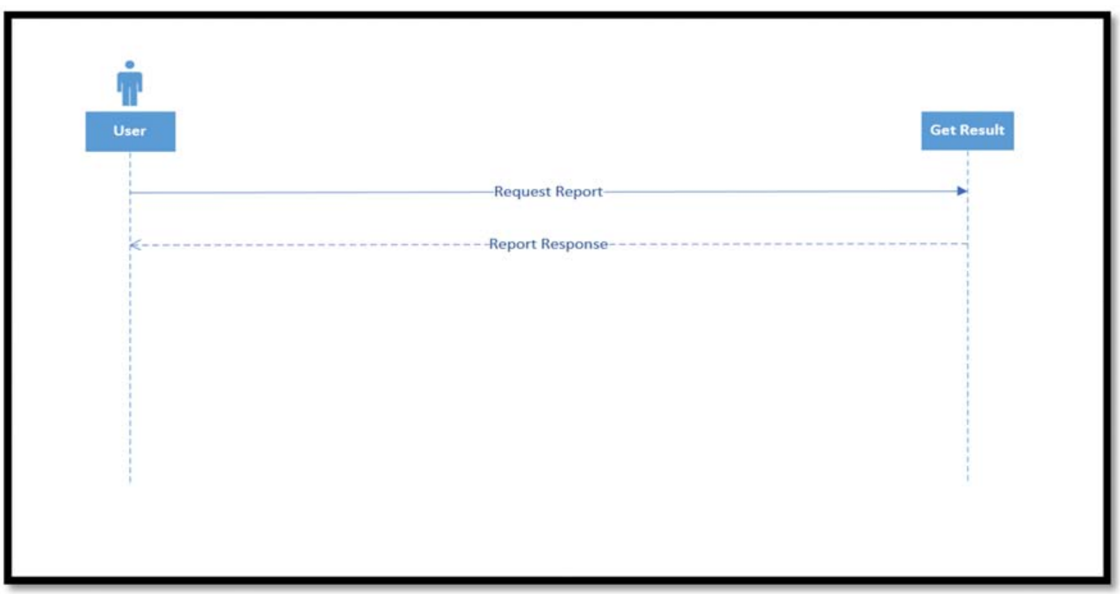

Figure 14: Getting Result Sequence Diagram

5.1.5 Activity Diagram

1. User Registration

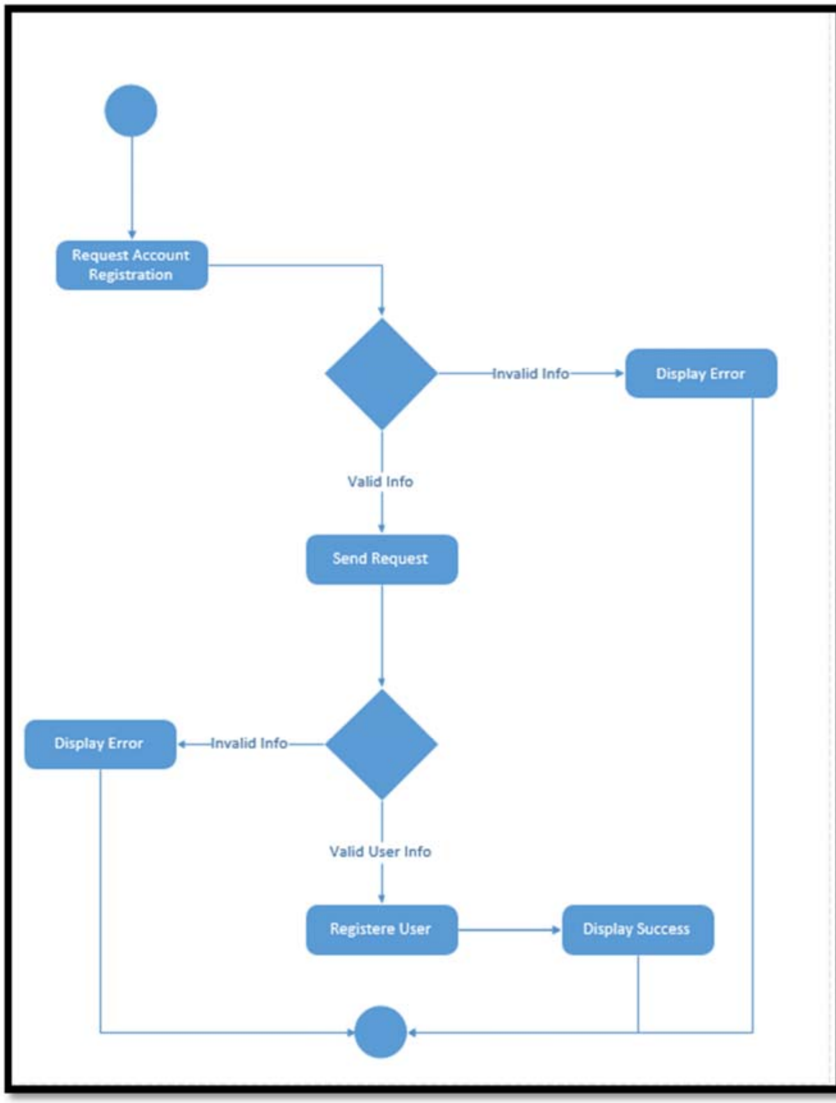

Figure 15: User Registration Activity Diagram

2. Login

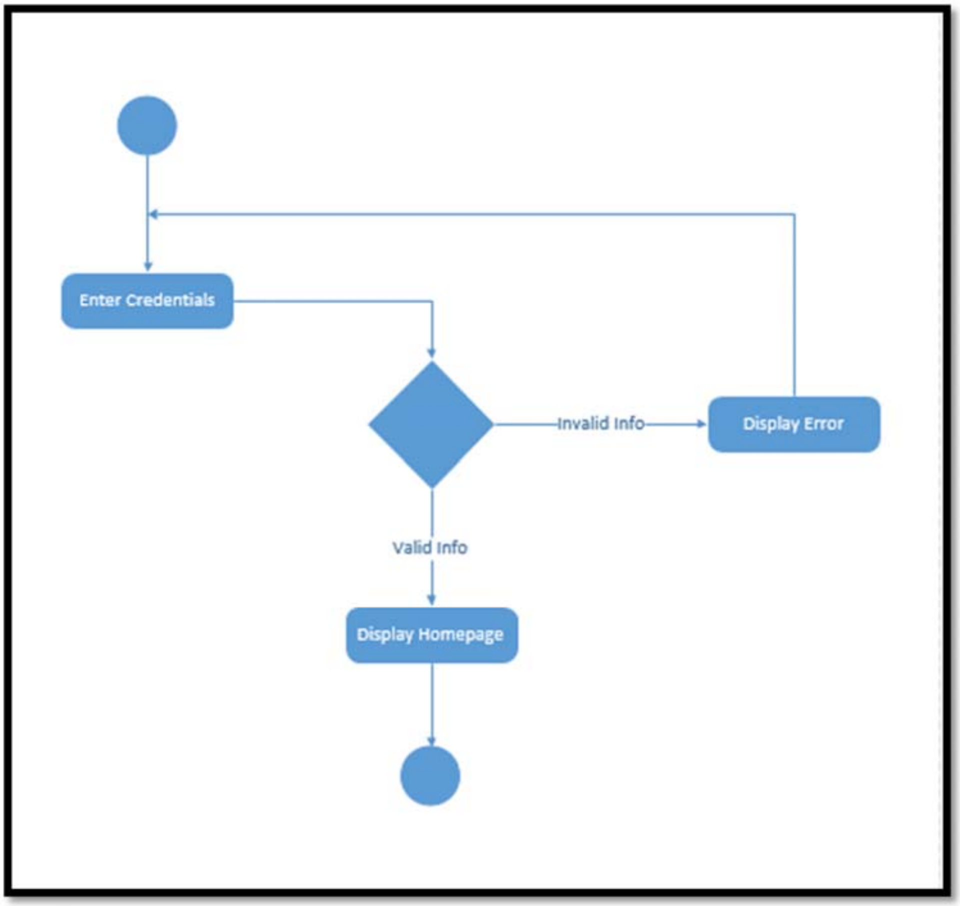

Figure 16: Login Activity Diagram

3. Upload File

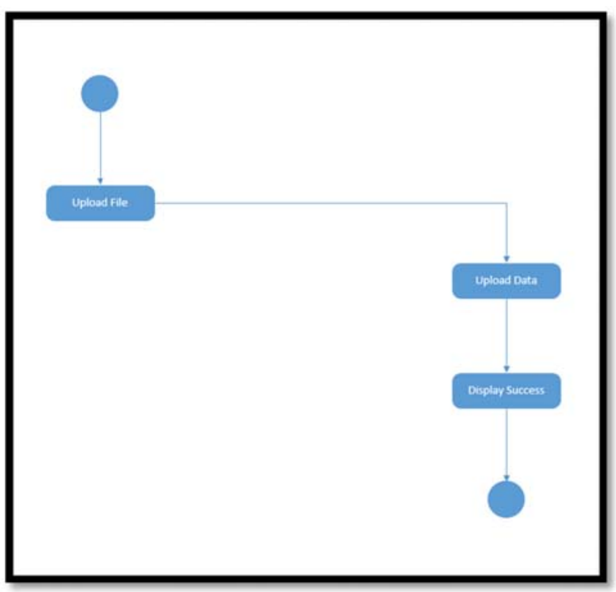

Figure 17: Upload File Activity Diagram

4. Get Result

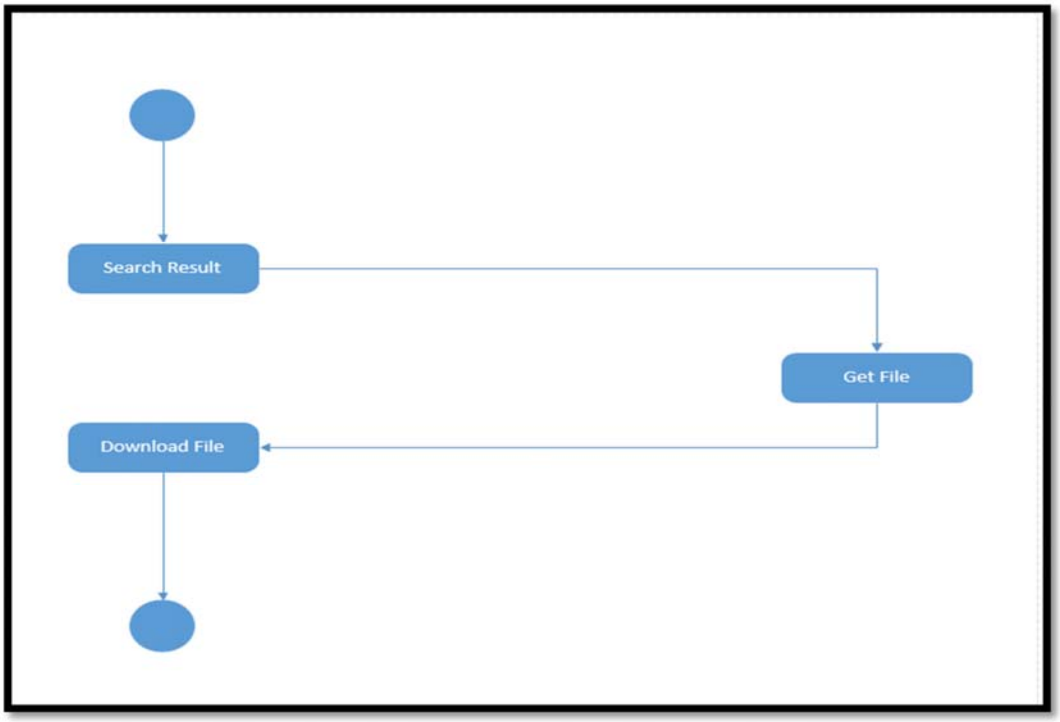

Figure 18: Getting Result Activity Diagram

5.2 DETAILED SYSTEM DESIGN

Most components described in the System Architecture section will require a more detailed discussion. Other lower-level components and sub-components may need to be described as well. Each subsection of this section will refer to or contain a detailed description of a system software component. The discussion provided should cover the following software component attributes:

5.2.1 Classification

The development of a brain tumor detection and localization system requires the implementation of various subsystems, modules, classes, packages, functions, and files. The image acquisition subsystem is a critical component that captures brain images through diverse imaging modalities, including magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET). The images that have been obtained are subjected to preprocessing in the subsystem dedicated to image processing. This is done to improve their quality, eliminate any unwanted noise or artifacts, and standardize their intensities.

The subsystem responsible for feature extraction obtains pertinent characteristics from the preprocessed images, including but not limited to shape, texture, and intensity features, with the aim of representing the images in a more concise and informative way. The aforementioned characteristics are subsequently inputted into the classification subsystem, which employs machine learning techniques such as support vector machines (SVM), artificial neural networks (ANN), and decision trees (DT) to categorize the images as either normal or tumor-present.

The localization subsystem employs various techniques, including region-growing, watershed segmentation, and thresholding, to determine the location and size of the brain tumor. The subsystem responsible for presenting the ultimate outcomes to the user is the visualization component, which showcases a 3D model or 2D images that are superimposed with the tumor's dimensions and placement.

The system's desired functionality is achieved through the implementation of various modules, classes, packages, functions, and files, which are responsible for performing specific tasks and communicating with each other. The image acquisition subsystem may comprise of various modules, such as DICOM, NIFTI, or MINC, to manage diverse image formats. Similarly, the feature extraction subsystem may utilize classes such as Gabor filters, local binary patterns (LBP), or wavelet transforms to extract image features. The classification subsystem may incorporate various functions, such as cross-validation, model selection, and hyperparameter tuning, to enhance the efficacy of the machine learning algorithms.

5.2.2 Definition

The primary purpose of BTDLI is to detect and localize brain tumors using MRI images. The system is designed to reduce human errors and provide medical practitioners and hospitals with accurate and efficient analysis of MRI scans.

5.2.3 Responsibilities

The main duty of the Brain Tumor Detection and Localization Initiative (BTDLI) is to conduct an analysis of magnetic resonance imaging (MRI) scans in order to identify and pinpoint the location of brain tumors. The mechanism achieves this objective through the utilization of machine learning algorithms that mimic intelligent human behavior. BTDLI offers precise and effective analysis of MRI scans to healthcare professionals and medical facilities, thereby mitigating the risk of diagnostic errors in the identification of brain tumors.

5.2.4 Constraints

The BTDLI framework may be subject to various constraints, such as assumptions, limitations, or restrictions pertaining to factors such as timing, storage, or component state. The system may possess limitations pertaining to the duration necessary for the analysis of an MRI image or the storage capacity essential for preserving the data produced by the system. The system may be subject to limitations pertaining to the structure of the input data, the precision of the output data, and the safeguarding of the system.

5.2.5 Composition

The Brain Tumor Detection and Localization using Image processing (BTDLI) system is comprised of several interdependent sub-components or modules that collaborate to examine Magnetic Resonance Imaging (MRI) scans and identify malignant growths in the brain. The constituent elements of the system may comprise of machine learning algorithms, image processing algorithms, and user interface components.

5.2.6 Uses/Interactions

The BTDLI system has been specifically developed for utilization by healthcare professionals and medical facilities. The system has the potential to engage with other constituents of a broader medical imaging or healthcare system, such as a patient database or an electronic health record system.

5.2.7 Resources

The proper functioning of BTDLI may necessitate the allocation of resources such as memory, processors, and databases. The system has the potential to oversee and impact extrinsic resources, including but not limited to printers and supplementary software libraries. Inadequate handling of race conditions and deadlock scenarios during system design can lead to their occurrence.

5.2.8 Processing

BTDLI processes MRI images using machine learning and image processing algorithms. The system may change its state based on the data it receives, and may also handle exceptions or errors that occur during processing. The system's algorithms should be designed with consideration for time and space complexity, as well as concurrency and scalability.

5.2.9 Interface/Exports

The BTDLI offers a comprehensive range of tools, materials, information, classifications, procedures, and anomalies that enable the analysis of magnetic resonance imaging (MRI) scans for the identification of neoplastic growths in the brain. The interface of the system may comprise a user interface element that facilitates the input of data by medical professionals and enables them to visualize the output generated by the system. The design of the system's interface should take into account various factors such as the system's classification, definition, responsibilities, constraints, composition, uses/interactions, resources, and processing.

5.3 User Interface Design

5.3.1 User Interface

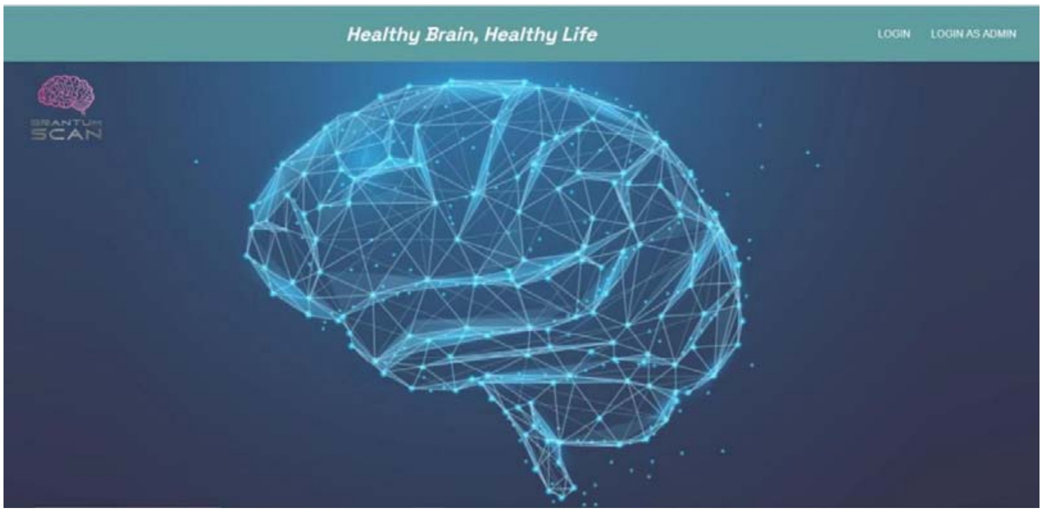

Figure 19: Basic User Interface

Figure 20: Login Interface

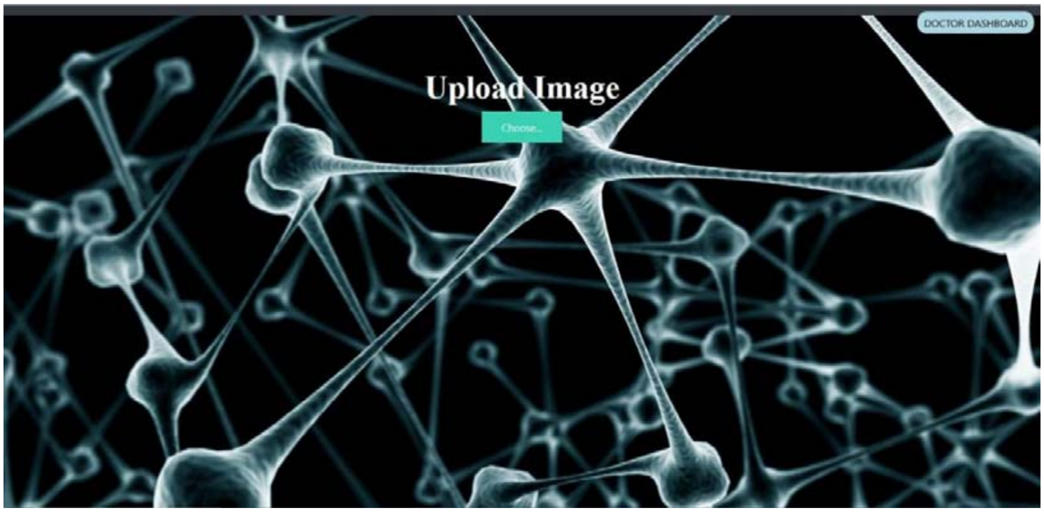

Figure 21: Uploading Image Interface

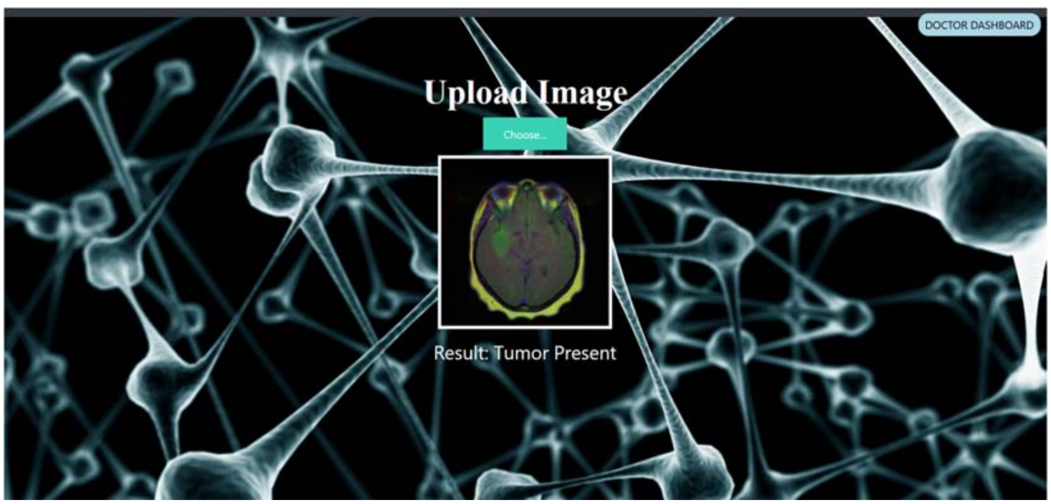

Figure 22: Choosing File Interface

5.3.2 Hardware Interface

As it will be a Web-App so no specific hardware interface required it would be easily accessible via devices.

5.3.3 Software Interface

Python is a general-purpose programming language that is interpreted and operates at a high level. The design philosophy of Python prioritizes the readability of code, which is achieved through its distinctive utilization of significant indentation. The language structure and object-oriented methodology of this programming language are designed to facilitate the creation of coherent and rational code for projects of varying sizes. Python is a programming language that features dynamic typing and garbage collection. The software facilitates the utilization of various programming paradigms, such as structured, object-oriented, and functional programming.

The Python programming language is frequently characterized as a "batteries included" language owing to its all-encompassing standard library.

5.3.4 Communication Interface

Internet connection is not required for the users to use the application, as the gestures in the predefined dataset will be accessed.

Chapter No.06

IMPLEMENTATION AND TESTING

6.1 OVERVIEW OF WORK

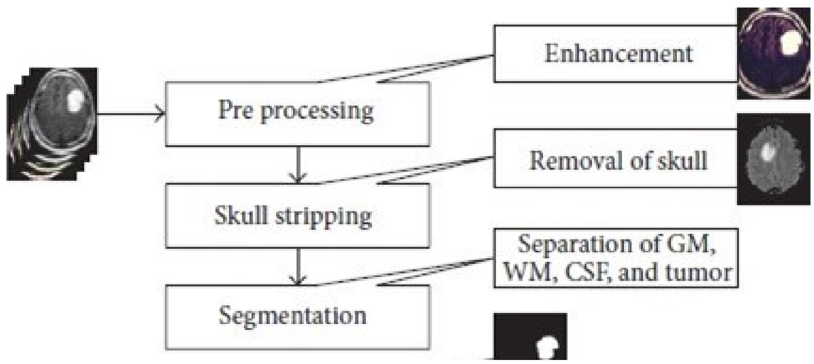

Figure 23: Workflow Overview

- **Image Preprocessing**: The system's input comprises of MRI and scanned images that may contain noise. Hence, our primary objective is to eliminate any unwanted disturbances from the input image. As delineated in the system flow, a high pass filter is being utilized for the purposes of noise reduction and preprocessing.
- **Segmentation:** Region growing is a straightforward technique for image segmentation based on regions. The technique in question is categorized as a pixel-based image segmentation method, as it entails the selection of seed points at the outset.
- **Tumor Identification:** In the current stage, we are utilizing a pre-existing dataset of brain MRIs to extract features. A knowledge base has been established for the purpose of conducting comparisons.

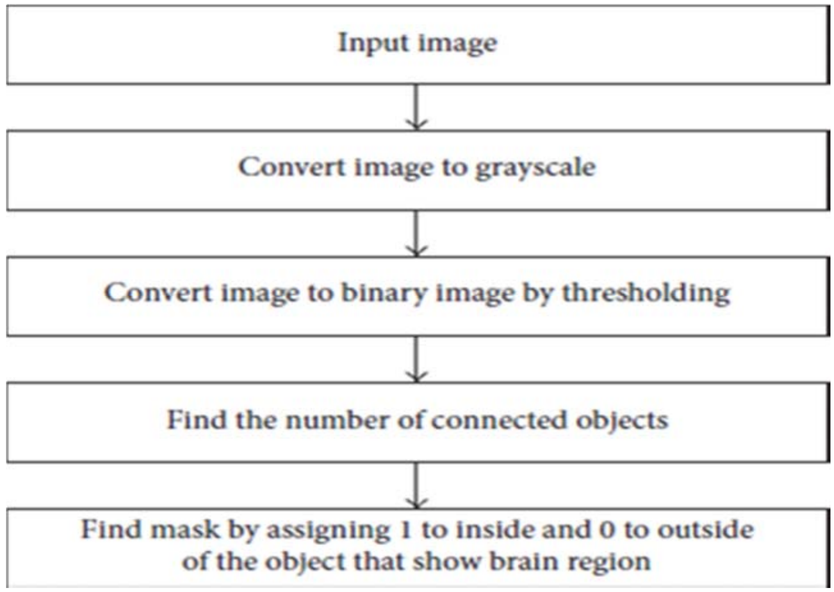

Figure 24: Steps Of Workflow

- In the initial stage, an image can be utilized as an input. The image utilized solely adipose and aqueous tissues alongside a tumor.
- The second step involves converting the image to grayscale.

  The concept of signal-to-noise ratio. The challenges associated with image processing include the intricacy of the code, the acquisition of knowledge related to image processing, and the complexity of visualizing the results. The complexity of color is a notable aspect.
- Subsequently, the image is transformed into a binary image through the process of thresholding. The process of thresholding is a fundamental technique in image segmentation, commonly employed to convert a grayscale image into a binary image. Thresholding involves the selection of a threshold value, followed by the determination of a corresponding gray level value. Instances that fall below the designated threshold value are categorized as 0, while those that are equal to or greater than the threshold value are classified as 1.
- Determine the quantity of interconnected entities.
- To identify the mask, designate a value of 1 to the interior of the object that displays the brain region, and a value of 0 to its exterior.

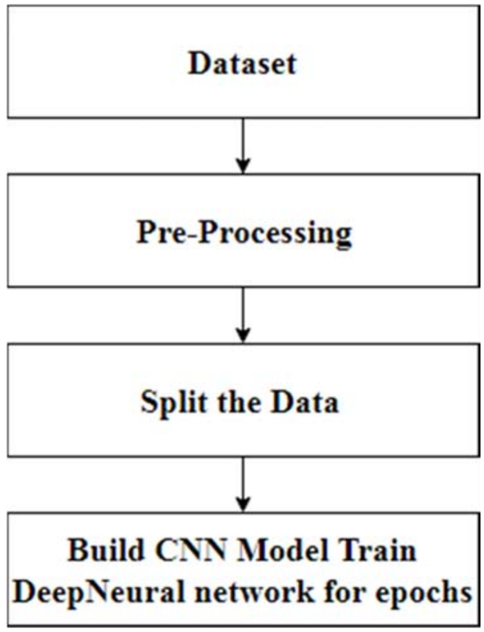

Figure 25: Working Procedure

The system under consideration comprises of five primary modules. The topics of interest are dataset and pre-processing. The data should be divided into appropriate subsets, followed by the construction of a Convolutional Neural Network model. The model should then be trained for a specified number of epochs, after which it can be used for classification purposes. Multiple MRI images can be selected from a dataset, with one serving as the input image. During the pre-processing stage of image analysis, the label is encoded and the image is resized. When splitting the data, the image is allocated to 80% for Training Data and 20% for Testing Data. Subsequently, construct a Convolutional Neural Network architecture and proceed to train a deep neural network for a specified number of epochs.

6.2 Working of CNN model

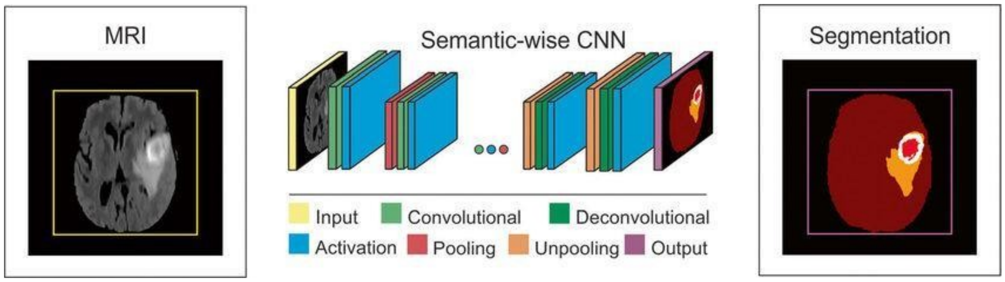

Figure 26: CNN Model

The Convolutional Neural Network (CNN) is a category of artificial neural network that is frequently employed in computer vision applications, including but not limited to image classification and object recognition. Convolutional neural networks (CNNs) are comprised of multiple layers, each of which serves a distinct purpose. The strata commonly comprise of convolutional strata, pooling strata, and fully connected strata.

The fundamental operation of a Convolutional Neural Network (CNN) can be elucidated through the subsequent stages:

- The initial layer of a Convolutional Neural Network (CNN) is referred to as the input layer, where the image or data to be analyzed is received.
- The Convolutional Layer involves the application of a group of filters, also referred to as kernels, to the input image. The convolution process involves the application of a filter to an image, whereby a dot product is computed between the filter and the corresponding portion of the image that it is currently covering. The aforementioned process produces a feature map that accentuates the salient characteristics of the given image.
- The Rectified Linear Units (ReLU) layer is utilized in neural networks to introduce non-linearity. The Rectified Linear Unit (ReLU) applies an activation function to the feature maps in an element-wise manner, resulting in the conversion of all negative values to zero.
- The Pooling Layer is responsible for reducing the size of feature maps through the use of pooling operations, such as max-pooling or average pooling. These operations select the maximum or average value from a specific region of the feature map.

- The fully connected layer is a crucial component of convolutional neural networks. It operates on the flattened output of the pooling layer and applies one or more fully connected layers. These layers execute a dot product between the input and a set of weights to process the data.
- The ultimate layer of the neural network produces the output, commonly in the form of a probability distribution that encompasses various categories in a classification assignment.

  In essence, the primary objective of a Convolutional Neural Network (CNN) is to acquire and isolate significant features from images or other forms of data, which can subsequently be applied to a range of functions including but not limited to object identification, image partitioning, and categorization.

6.1 Working of U-Net Model

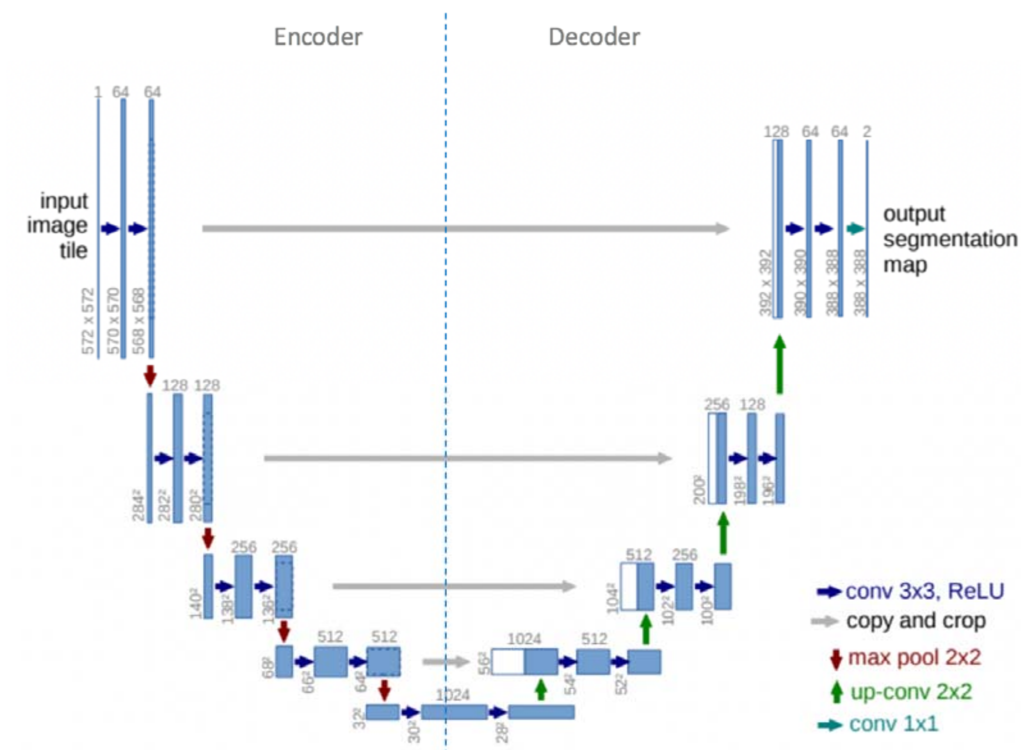

Figure 27: U-Net Model

The U-Net is a convolutional neural network architecture that was specifically designed for the purpose of image segmentation, with a particular focus on biomedical image segmentation. The U-Net architecture derives its name from its distinctive U-shaped configuration, comprising of an encoding pathway and a decoding pathway.

The fundamental operation of a U-Net model can be elucidated through the subsequent steps:

- The initial stage of the U-Net framework is referred to as the encoding path, which comprises of a sequence of convolutional layers succeeded by max pooling layers. The layers in question are tasked with the extraction of features from the input image and the subsequent reduction of its spatial dimensions.

- The decoding path, constituting the latter half of the U-Net architecture, is a symmetrical counterpart of the encoding path, aimed at decoding the encoded features. The process of decoding involves a sequence of up-convolutional layers, which are subsequently concatenated with the corresponding feature maps from the encoding path. The up-convolutional layers are responsible for augmenting the spatial resolution of the feature maps. In addition, the concatenation operation is utilized to maintain the spatial information that may have been lost during the encoding stage.
- The skip connections constitute a crucial element of the U-Net framework, serving to establish a connection between the corresponding layers of the encoding and decoding pathways. The utilization of skip connections in U-Net architecture facilitates the integration of low-level and high-level features, thereby enhancing the precision of segmentation.
- The ultimate layer of the U-Net architecture is a convolutional layer with a dimension of 1x1, which produces the segmentation mask. The final layer of the model generates a probability map, which assigns a probability score to individual pixels, denoting the probability of that pixel being associated with a specific class.

In general, the U-Net architecture is a robust framework for the purpose of image segmentation, with a specific emphasis on biomedical image segmentation, wherein it has demonstrated exceptional performance and attained the highest level of achievement. The widespread adoption of skip connections in computer vision applications can be attributed to its capacity to effectively integrate low-level and high-level features.

Chapter No.07

RESULTS AND DISCUSSION

7.1 Data Set

7.1.1 Patient population:

The present investigation sourced its data from two repositories, namely The Cancer Genome Atlas (TCGA) and The Cancer Imaging Archive (TCIA). A total of 120 patients were identified from the TCGA lower-grade glioma collection, all of whom possessed preoperative imaging data that included a fluid-attenuated inversion recovery (FLAIR) sequence. Ten participants were excluded from the study due to the unavailability of their genomic cluster information. The cohort of 110 participants included individuals from five distinct institutions, namely Thomas Jefferson University (TCGA-CS, n=16), Henry Ford Hospital (TCGA-DU, n=45), UNC (TCGA-EZ, n=1), Case Western (TCGA-FG, n=14), and Case Western – St. Joseph's (TCGA- HT, n=34), all of whom were sourced from the TCGA LGG collection. The comprehensive roster of patients utilized in this investigation has been incorporated in Online Resource 1. The cohort of 110 individuals was partitioned into 22 distinct and mutually exclusive groups, each containing 5 individuals. This procedure was conducted for the purpose of evaluation utilizing cross-validation.

7.1.2 Imaging data:

The present study utilized imaging data sourced from The Cancer Imaging Archive, a repository of images associated with TCGA patients that is supported by the National Cancer Institute. All available modalities were utilized, with FLAIR being the sole modality employed in the absence of any others. The study included a total of 101 patients who had complete sequences available for analysis. Additionally, there were 9 patients who had a missing post-contrast sequence and 6 patients who had a missing pre-contrast sequence. Online Resource 1 contains a comprehensive compilation of all the available sequences for each patient. The quantity of slices exhibited inter-patient variability, ranging from 20 to 88. The analysis solely focused on preoperative data to accurately capture the initial tumor growth pattern. The evaluation of neoplasm morphology relied on FLAIR abnormality as the occurrence of enhancing tumor in LGG is infrequent. A medical school graduate with expertise in neuroradiology imaging, employed as a researcher in our laboratory, performed manual annotation of FLAIR images. This involved outlining the FLAIR abnormality on each slice to generate training data for the automatic segmentation algorithm. The software utilized in this study was developed within the confines of our laboratory. All annotations were verified and corrected by a radiologist who is eligible for board certification. The dataset utilized in our study comprises of registered images and corresponding manual segmentation masks.

7.1.3 Genomic data:

The study utilized genomic data encompassing DNA methylation, gene expression, DNA copy number, microRNA expression, and IDH mutation 1p/19q co-deletion measurement. In our analysis, we specifically examine six molecular classifications of LGG that have been previously identified and are known to exhibit correlation with certain tumor shape features .

- The molecular subtype of the sample was determined based on the presence or absence of IDH mutation and 1p/19q co-deletion. Three subtypes were identified: IDH mutation-1p/19q co-deletion, IDH mutation without 1p/19q co-deletion, and IDH wild type.
- The study utilized RNA sequencing to identify four distinct clusters, which were labeled as R1 through R4.
- There are five clusters of DNA methylation, which are denoted as M1-M5.
- There are four distinct clusters of DNA copy numbers, with three of them being labeled as C1, C2, and C3.
- The study identifies five distinct clusters of microRNA expression, with four of them being labeled as mi1 through mi4.The phenomenon under consideration involves six clusters, which can be further divided into three distinct clusters denoted as coc1, coc2, and coc3.

7.2 TOOLS & TECHNOLOGY USED

Python was chosen as the programming language for this project. This call was deemed straightforward due to several factors.

- Python is a programming language that benefits from a large and diverse community of users. The resolution of any encountered issues can be easily attained by consulting Stack Overflow. Python is a highly popular programming language, which increases the likelihood of obtaining prompt solutions to inquiries on the platform.
- Python offers a plethora of robust tools specifically designed for scientific computing. Freely available and well-documented packages such as NumPy, Pandas, and SciPy are at one's disposal. These software packages have the potential to significantly reduce the amount of code necessary to develop a particular program and alter its structure.This facilitates rapid iteration.
- The Python programming language is characterized by its forgiving nature, allowing for the creation of programs that resemble pseudo code. The utilization of this approach may prove advantageous in cases where the pseudo code presented in instructional literature necessitates implementation and validation. In certain cases, accomplishing this step can be relatively effortless through the utilization of Python. Nevertheless, Python is not exempt from encountering errors. The programming language is characterized by dynamic writing, and software modules are notorious for containing poorly written code. Encountering a scenario where a package method yields an object that appears to be an array but lacks the characteristics of a true array can be a source of frustration.
- In addition to the observation that the conventional Python documentation lacks explicit declaration of a method's return type, this may result in a substantial amount of experimentation and debugging that would not be necessary in a more robustly composed programming language. This issue hinders the acquisition of proficiency in utilizing an alternative Python package or library, rendering the process more challenging than it would otherwise be.

The **Jupyter Notebook** is a freely available web-based tool that facilitates the creation and dissemination of documents that incorporate executable code, mathematical expressions, graphical representations, and explanatory text. The applications of this technology encompass a wide range of tasks, such as data cleansing and manipulation, numerical emulation, statistical analysis, data representation, artificial intelligence, and numerous other functions.

Noise removal and sharpening techniques involve the application of filters to eliminate undesired data from an image. A sharpened and black-and-white grayscale image may serve as an input.

The morphological operations of **erosion and dilation** are typically utilized on binary images, although various adaptations exist that enable their application to grayscale images. The fundamental impact of the operator applied to a binary image is the gradual erosion of ground pixels towards the boundaries of regions.

Negation is a photographic technique that involves the use of a transparent plastic film strip or sheet to create an image. This technique results in the reversal of tones, where the lightest areas of the photographed subject appear darkest and the darkest areas appear lightest.

The process of image **subtraction** involves the numerical subtraction of one pixel or an entire image from another image in a digital format. The non-pigmented region of the neoplasm may be extracted by subtracting it from the remaining pigmented area depicted in the images.

Thresholding is a fundamental technique utilized in image segmentation. It involves the process of separating an image into distinct regions based on a predetermined threshold value. The process involves the conversion of a grayscale image to a binary image.

Boundary detection is a method that can be utilized to accurately determine the total area or boundary of a given object. The white portion of tumor tissues can be effectively delineated and its precise boundary can be identified. The calculation of the size and shape occupied by tumor tissues is a valuable method.

7.3 Model Evaluation

7.3.1 Training and validation accuracy :

The assessment of a machine learning model's performance involves the use of two metrics, namely training accuracy and validation accuracy.

The term "training accuracy" pertains to the level of accuracy exhibited by a model on the specific dataset it was trained on. In the process of training, the model is exposed to a collection of data that has been labeled, and it proceeds to modify its internal parameters in order to reduce the discrepancy between the predicted and observed labels. During the training process, the model's performance on the training data generally enhances, leading to an increase in the training accuracy. The accuracy of a model on a distinct dataset that was not employed during the training process is known as validation accuracy.

The aforementioned dataset is commonly withheld from the training data and employed for the purpose of evaluating the model. Through the process of assessing the model's performance on data that has not been previously encountered, we can make an estimation of its capacity to generalize to novel data.

Ideally, the similarity between the validation accuracy and the training accuracy indicates that the model is capable of generalizing well to new data and is not overfitting to the training data. When the training accuracy significantly exceeds the validation accuracy, it is possible that the model is overfitting to the training data and lacks the ability to generalize effectively. In this instance, it may be necessary to modify the model's architecture or regularization methods to enhance its efficacy on unobserved data.

The graph below is showing our project Training and Validation Accuracy with best Epoch of 82.

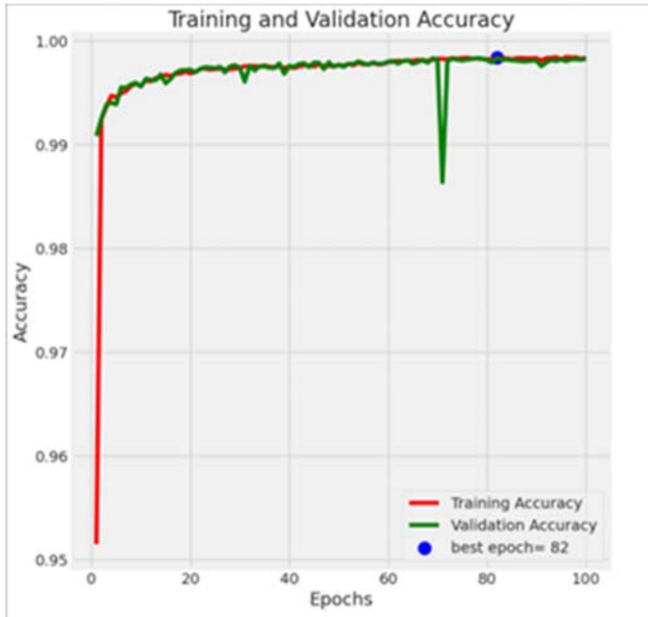

Figure 28: Training and Validation Accuracy Graph

7.3.2 Training and validation IOU coefficient :

The process of acquiring proficiency in the Intersection over Union (IOU) coefficient and its validation. The IOU coefficient comprises two metrics that are employed to assess the efficacy of a machine learning model in image segmentation tasks.

The IOU coefficient serves as a metric for evaluating the degree of alignment between the predicted segmentation mask and the ground truth mask. The metric is determined by dividing the common area of the predicted and actual masks by their combined area.

The term "Training IOU coefficient" pertains to the IOU coefficient that is calculated based on the training dataset. In the course of training, the model is exposed to a collection of labeled images, and subsequently, the predicted segmentation masks are evaluated against the corresponding ground truth masks.

The model optimizes its internal parameters to minimize the discrepancy between the predicted and observed masks. As the training of the model progresses, it is common for the IOU coefficient to exhibit an upward trend, which signifies an enhancement in its efficacy on the training dataset.

Validation The IOU coefficient, in contrast, pertains to the IOU coefficient that has been calculated on an independent dataset that was not utilized in the training process. The aforementioned dataset is commonly withheld from the training data and employed for the purpose of evaluating the model. Through the process of assessing the model's performance on unobserved data, it is possible to approximate its capacity to extend to novel images that have not been previously encountered.

Ideally, it is desirable for the validation IOU coefficient to be comparable to the training IOU coefficient, as this suggests that the model is not exhibiting overfitting tendencies towards the training data and is capable of effectively generalizing to novel data. When the training IOU coefficient significantly exceeds the validation IOU coefficient, it is possible that the model is overfitting to the training data and may not be capable of generalizing effectively. In this instance, it may be necessary to modify the model's architecture or regularization methods to enhance its efficacy on unobserved data.

Figure 29: Training and Validation IoU Coefficient Graph

7.3.3 Training and validation Dice coefficient :

Training The topic of interest pertains to the Dice coefficient and its application in validation. The Dice coefficient comprises two metrics that are commonly employed to assess the efficacy of a machine learning model in the context of image segmentation tasks.

The Dice coefficient is a metric utilized to evaluate the degree of concurrence between the predicted segmentation mask and the ground truth mask.

The metric is derived by computing twice the intersection of the predicted and ground truth masks, and subsequently dividing the result by the sum of the pixels in both masks.

The term "Training Dice coefficient" denotes the computation of the Dice coefficient on the dataset used for training. In the course of training, the model is exposed to a collection of images that have been labeled, and subsequently, the segmentation masks that are predicted by the model are juxtaposed with the ground truth masks. The model optimizes its internal parameters to minimize the discrepancy between the predicted and observed masks. As the training process progresses, it is common for the Dice coefficient to exhibit an upward trend, which suggests an enhancement in the model's efficacy on the training dataset.

Validation The Dice coefficient pertains to the computation of the Dice coefficient on an independent dataset that was not utilized during the training phase. The aforementioned dataset is commonly withheld from the training data and employed for the purpose of assessing the performance of the model. Through the assessment of the model on unobserved data, it is possible to approximate its capacity to generalize to novel images that have not been previously encountered.

Ideally, the Dice coefficient for validation should exhibit similarity to the Dice coefficient for training, thereby indicating that the model is not overfitting to the training data and is capable of generalizing effectively to novel data. When the Dice coefficient for training data is significantly greater than that for validation data, it may suggest that the model is overfitting to the training data and lacks the ability to generalize effectively. In this instance, it may be necessary to modify the model's architecture or regularization methods in order to enhance its efficacy on unobserved data.

Figure 30: Training and Validation Dice Coefficient Graph

7.3.4 Training and validation Loss :

The assessment of a machine learning model's performance during the training process involves the utilization of two metrics, namely training loss and validation loss.

The term "training loss" pertains to the discrepancy or expense linked with the model's forecasts on the training dataset. In the process of training, the model is provided with a collection of annotated data, and it adapts its internal parameters to minimize the dissimilarity between its anticipated outputs and the actual labels. As the model continues to train, the training loss typically decreases, indicating that the model is improving its ability to make accurate predictions on the training data.

The term "validation loss" pertains to the degree of inaccuracy or expense linked to the model's prognostications on an independent dataset that was not employed during the training phase. The aforementioned dataset is commonly withheld from the training data and utilized for the purpose of evaluating the model. Through the process of assessing the model's performance on data that has not been previously encountered, we can infer its capacity to extrapolate to novel data.

Ideally, the congruence between the validation loss and the training loss should be observed, which suggests that the model is not excessively fitting to the training data and has the ability to generalize effectively to novel data. When the training loss is significantly lower than the validation loss, it is possible that the model is overfitting to the training data and lacks the ability to generalize effectively. In this instance, it may be necessary to modify the model's architecture or employ regularization techniques in order to enhance its efficacy when applied to unobserved data.

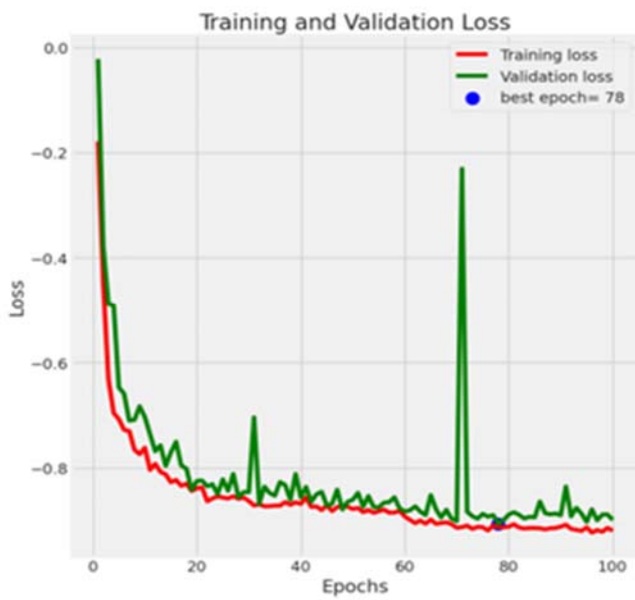

Figure 31: Training and Validation Loss

We have given 393 images for test purpose to test our model’s performance, it yielded 91%. The dice coefficient accurately depicts model’s performance because it matches how well our model outlined and segmented the tumor, with actually segmented tumor by a radiologist.

```
131/131 [==============================] - 122s 936ms/step - loss: -0.9253 - accuracy: 0.9985 - iou_coef: 0.8618 - dice_coef: 0.9253
131/131 [==============================] - 41s 311ms/step - loss: -0.8913 - accuracy: 0.9982 - iou_coef: 0.8055 - dice_coef: 0.8913
Found 393 validated image filenames.
Found 393 validated image filenames.
131/131 [==============================] - 44s 334ms/step - loss: -0.9091 - accuracy: 0.9980 - iou_coef: 0.8346 - dice_coef: 0.9092
Train Loss:  -0.9253336191177368
Train Accuracy:  0.9985136389732361
Train IoU:  0.8617569804191589
Train Dice:  0.9253110885620117
--------------------
Valid Loss:  -0.8913013339042664
Valid Accuracy:  0.9981948137283325
Valid IoU:  0.8055282831192017
Valid Dice:  0.8912923336029053
--------------------
Test Loss:  -0.9090806841850281
Test Accuracy:  0.9980402588844299
Test IoU:  0.8346399664878845
Test Dice:  0.9092006087303162
```

Figure 32: Results

7.4 Test Cases

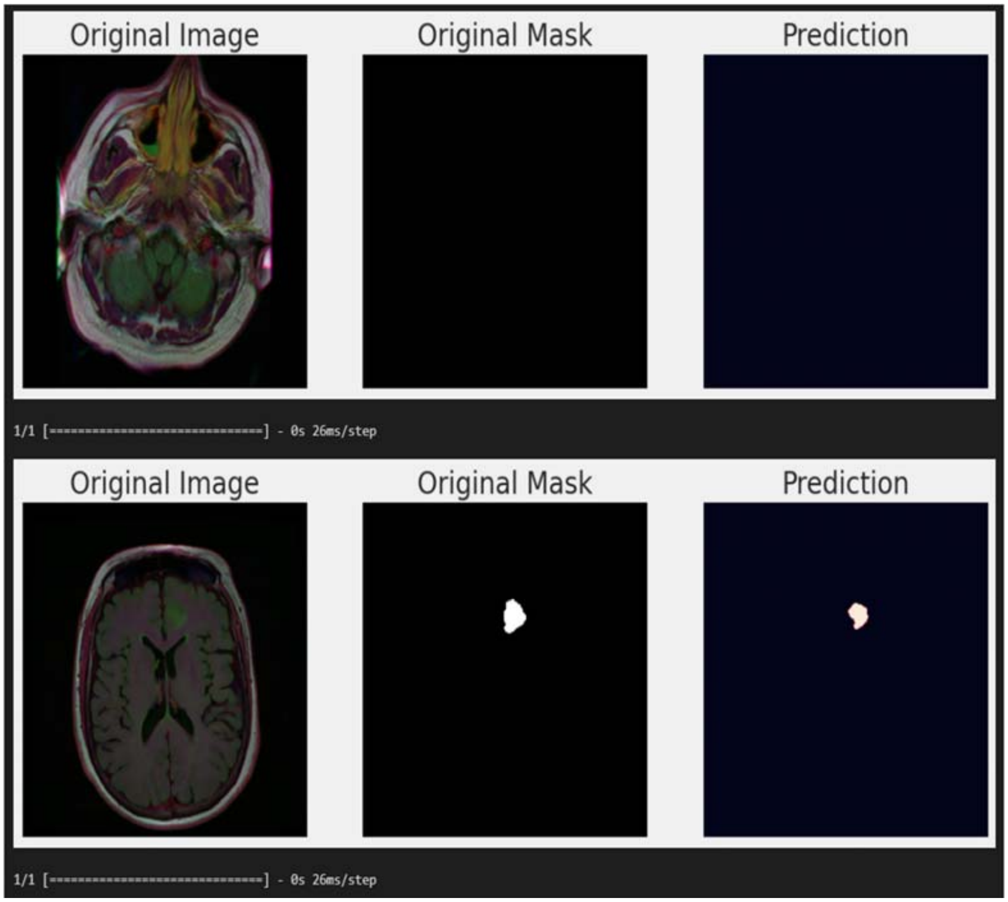

Figure 33: Test Case 1

In the first image above there is no tumor so our model has represented that there is no tumor.

In the second image tumor is present so our model has localized the tumor almost same as the original mask.

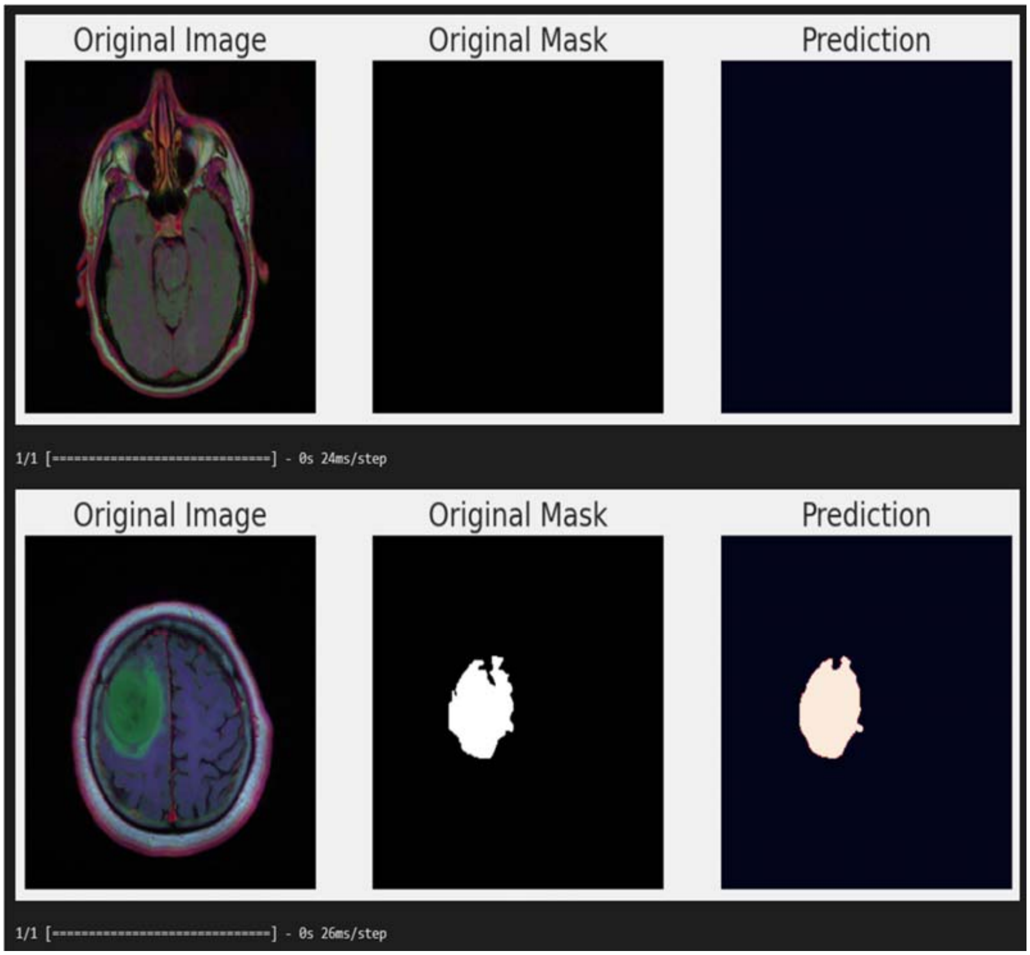

Figure 34: Test Case 2

In the first image above there is no tumor so our model has represented that there is no tumor.

In second image tumor is present so our model has localized the tumor almost same as the original mask.

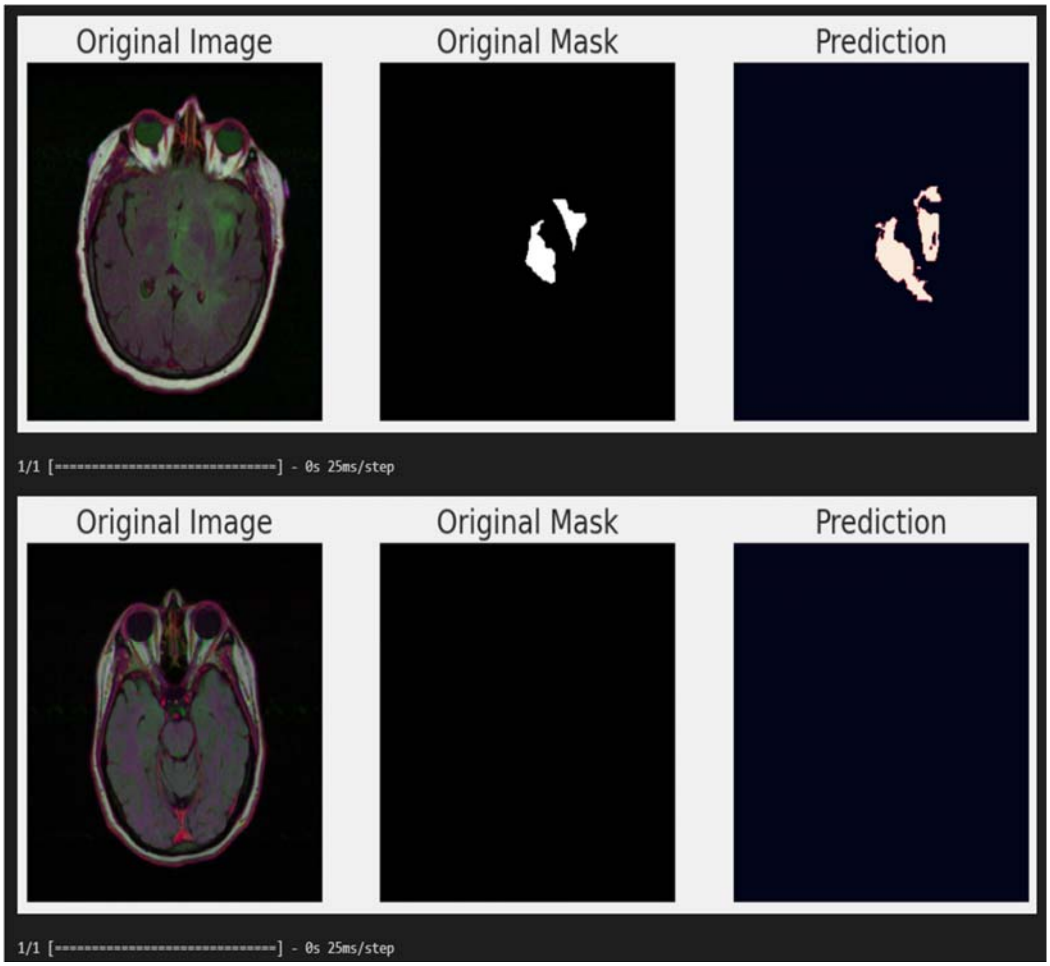

Figure 35: Test Case 3

In the first image above tumor is present so our model has localized the tumor almost same as the original mask.

In the second image there is no tumor so our model has represented that there is no tumor.

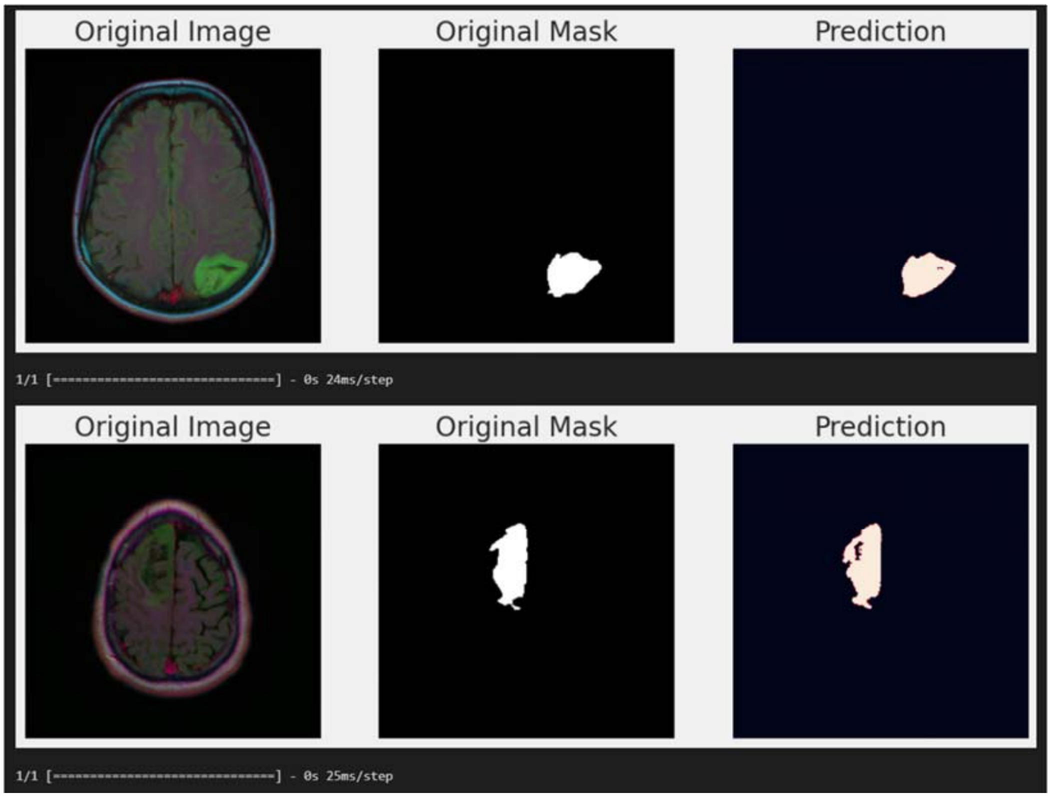

Figure 36: Test Case 5

Here In both of the images above tumor is present so our model has localized the tumor almost same as the original mask.

7.5 APPLICATION

- The main aim of the applications is tumor identification.
- The main reason behind the development of this application is to provide proper treatment as soon as possible and protect the human life which is in danger.
- This application is helpful to doctors as well as patient.
- The manual identification is not so fast, more accurate and efficient for user. To overcome those problem this application is design.
- It is user friendly application.

Chapter No. 08

CONCLUSION AND FUTURE WORK

The study concludes that the utilization of deep learning algorithms for the automatic extraction of MRI features was found to be associated with the molecular subtypes of lower-grade gliomas as determined by genomic assays. The findings suggest potential for the development of imaging-based surrogates that are reproducible and non-invasive for the purpose of assessing tumor genomics in cases of brain cancer. On numerous occasions, it may prove to be an insurmountable challenge for a medical practitioner, even one with considerable expertise, to accurately diagnose a brain tumor based solely on its distinctive features. Additional criteria are required to make a clinical diagnosis. The diagnostic procedure can be executed independently, albeit its accuracy may not be consistently dependable. The process involves utilizing an MRI device to examine its characteristics and ascertain the presence or absence of brain tumors. The development of automated methods is imperative to enhance diagnostic accuracy, particularly for individuals lacking access to a radiologist and cases where even a trained observer may produce erroneous results.

8.1 Future Work

Several prospective avenues for future research could be explored to enhance the efficacy of the model.

- The task of detecting brain tumors poses a significant challenge, and the efficacy of the model utilized is contingent upon the caliber and quantity of the data utilized for training purposes. Therefore, **expanding the dataset** is crucial for improving the accuracy of brain tumor detection models. To enhance the performance of your model, it is advisable to contemplate augmenting your dataset by incorporating additional brain tumor images that exhibit varying sizes, shapes, and locations. One may also contemplate the inclusion of visuals procured from various origins as a means of augmenting the heterogeneity of their data.

- **Transfer learning** is a widely adopted approach aimed at enhancing the efficacy of deep learning models. One potential approach to consider is the utilization of a pre-existing U-Net model, specifically one that has been trained on the ImageNet dataset. This model could be fine-tuned on the brain tumor dataset in question. The implementation of this technique has the potential to enhance the efficacy of the model, while concurrently decreasing the duration of the training process.
- **Ensembling** is a methodology that involves the amalgamation of multiple models to enhance the overall performance. One potential approach to improve the segmentation mask generation is to train multiple U-Net models with varying hyperparameters or on distinct subsets of the data, and subsequently integrate their outputs to produce the ultimate segmentation mask. Incorporating this approach may lead to a decrease in variance and an enhancement in the precision of your model.
- **Clinical validation** studies can be conducted to assess the performance of a U-Net model developed for brain tumor detection in real-world scenarios. It is recommended to ensure that the model is robust before proceeding with clinical validation. Assessing the reliability and generalizability of a model can aid in evaluating its potential for clinical application.
- The detection of brain tumors usually necessitates the amalgamation of diverse imaging modalities, including magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET). One potential avenue for enhancing the precision of your U-Net model and achieving a more thorough evaluation of brain tumors is to explore the **integration of additional modalities**.

Chapter 09

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