DEEP LEARNING BASED 3D MRI SEGMENTATION USING CNN ALGORITHM FOR DETECTING THE BRAIN TUMOUR

A PROJECT REPORT

Submitted by

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in partial fulfillment for the award of the degree

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BONAFIDE CERTIFICATE

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ABSTRACT

This study proposes a deep learning-based approach for the most precise brain tumor segmentation in medical images. Leveraging convolutional neural networks (CNNs), the model demonstrates robust performance in delineating tumor boundaries, providing a crucial tool for precise diagnosis and treatment planning in neuro-oncology. The methodology integrates advanced neural network architectures and explores optimization techniques to enhance segmentation accuracy, contributing to the ongoing efforts in leveraging AI for improved medical image analysis. By predicting the tumor based on their size, grade and the location in which it is present we can able to identify the type of the tumor present in the brain and the seriousness of the tumor .

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

S.NO	ACRONYMS	DESCRIPTION
1	CNN	Convolutional Neural Network
2	MRI	Magnetic Resonance Imaging
3	SGD	Stochastic Gradient Descent
4	GCNN	Gaussian Convolutional Neural Network.
5	SVM	Support Vector Machine

CHAPTER 1

INTRODUCTION

1.1 DOMAIN INTRODUCTION

Deep learning based 3d MRI segmentation using CNN algorithm for detecting the brain tumor. Brain tumor segmentation from 3D MRI data is a critical task in neuroimaging, as it provides valuable information for diagnosis, treatment planning, and monitoring of the disease progression.

Deep learning is a subfield of machine learning that focuses on algorithms inspired by the structure and function of the human brain's neural networks. It involves training artificial neural networks with large amounts of data to recognize patterns and make predictions or decisions. Deep learning algorithms consist of multiple layers of interconnected nodes, known as neurons, organized in a hierarchical manner.

Deep learning architectures include convolutional neural networks (CNNs) for image recognition. Deep learning has achieved remarkable success in various real-world applications, including image classification, and medical diagnosis.

Introducing a revolutionary Deep learning based 3d MRI segmentation using CNN algorithm for detecting the brain tumor. The ensures seamless learning, and innovative in identifying the tumor which enhances practical outcomes.

Develop a comprehensive system for advancements in medical imaging technology, particularly Magnetic Resonance Imaging (MRI), have revolutionized the diagnosis and treatment of various medical conditions, including brain tumors. Deep Learning (DL) techniques, especially.

Convolutional Neural Networks (CNNs), have emerged as powerful tools for automatic segmentation of medical images, offering remarkable accuracy and efficiency.

Creating a robust DL-based approaches offer the potential for automated and precise segmentation of brain tumors, thereby aiding clinicians in making faster and more accurate diagnoses. By leveraging large datasets of annotated MRI scans, DL models can learn complex patterns and features representative of different tumor types and their spatial distributions.

COMPONENTS OF BRAIN TUMOR DETECTION: EMPOWERING THE ACCURATE OUTPUT FOR IN THE DETECTION OF THE TUMOR PRESENT IN THE BRAIN.

The brain tumor detection: empowering the accurate output for the detection of the tumor present in the brain.

Convolutional Neural Network (CNN):

CNN, short for Convolutional Neural Network, is a specialized type of neural network primarily used for processing visual data like images. It employs convolutional layers to extract features and pooling layers to down sample them. With activation functions and fully connected layers, CNNs can perform tasks such as image classification and object detection, revolutionizing fields like computer vision and medical imaging.

Image Pre-processing:

Before feeding MRI scans into DL models, pre-processing steps such as skull stripping, intensity normalization, and spatial normalization are often performed to enhance the quality and consistency of the input data.

Model Architectures:

Various CNN architectures, such as U-Net, 3D U-Net, and V-Net, have been adapted and developed specifically for 3D MRI segmentation tasks. These models are designed to effectively capture spatial dependencies and hierarchical features within volumetric medical images.

Training and Validation:

Training DL models for MRI segmentation requires large, annotated datasets. These datasets are used to train the model parameters through optimization algorithms like stochastic gradient descent (SGD), while validation datasets ensure the generalization and robustness of the trained models.

Evaluation Metrics:

Performance evaluation of DL models is crucial for assessing their accuracy and efficacy. Common metrics for evaluating segmentation results include Dice Similarity Coefficient (DSC), Intersection over Union (IOU), sensitivity, specificity, and Harsdorf distance.

Clinical Applications:

DL-based 3D MRI segmentation has diverse clinical applications, including tumor localization, tumor volume estimation, treatment planning, and response assessment. Integrating these automated segmentation tools into clinical workflows can streamline diagnosis and improve patient outcomes.

1.2 PROBLEM DEFINITION

The problem addressed in this study is the accurate and efficient segmentation of brain tumors from 3D MRI scans using deep learning techniques, specifically Convolutional Neural Networks (CNNs). The overarching goal is to develop an automated system that can reliably detect and segment brain tumors from volumetric MRI data, thereby aiding clinicians in diagnosis and treatment planning.

The primary challenge is to achieve high segmentation accuracy, ensuring that the deep learning model accurately delineates tumor regions from surrounding brain tissues in 3D MRI volumes. This involves capturing intricate spatial patterns and features indicative of tumor presence while minimizing false positives and negatives.

Another key concern is the ability of the CNN algorithm to generalize across diverse patient populations and imaging conditions. The model should be robust enough to handle variations in MRI protocols, scanner types, and patient demographics, ensuring consistent performance across different datasets.

Obtaining large-scale annotated MRI datasets for training deep learning models poses a significant challenge. Annotating MRI scans with accurate tumor segmentations is time consuming and requires expertise. Moreover, ensuring the quality and consistency of annotated data is crucial for training robust models.

Computational Efficiency: 3D MRI volumes are computationally intensive, requiring substantial memory and processing power for model training and inference. Developing CNN architectures that balance accuracy with computational efficiency is essential for practical deployment in clinical settings. Addressing these challenges requires a comprehensive approach that encompasses data pre-processing, model development, training optimization, performance evaluation, and clinical validation. By tackling these issues, the proposed deep learning-based framework aims to provide clinicians with a reliable and efficient tool for brain tumor detection and segmentation from 3D MRI scans, ultimately improving patient care and outcomes in neuroimaging. A significant hurdle is the absence of real-time feedback mechanisms, which hinder learners progress by preventing them from promptly identifying and correcting errors.

1.3 PROJECT DESCRIPTION

The problem addressed in this study is the accurate and efficient segmentation of brain tumors from 3D MRI scans using deep learning techniques, specifically Convolutional Neural Networks (CNNs). The overarching goal is to develop an automated system that can reliably detect and segment brain tumors from volumetric MRI data, thereby aiding clinicians in diagnosis and treatment planning.

Segmentation Accuracy: The primary challenge is to achieve high segmentation accuracy, ensuring that the deep learning model accurately delineates tumor regions from surrounding brain tissues in 3D MRI volumes. This involves capturing intricate spatial patterns and features indicative of tumor presence while minimizing false positives and negatives.

Model Generalization: Another key concern is the ability of the CNN algorithm to generalize across diverse patient populations and imaging conditions. The model should be robust enough to handle variations in MRI protocols, scanner types, and patient demographics, ensuring consistent performance across different datasets.

Data Availability and Annotation: Obtaining large-scale annotated MRI datasets for training deep learning models poses a significant challenge. Annotating MRI scans with accurate tumor segmentations is time-consuming and requires expertise. Moreover, ensuring the quality and consistency of annotated data is crucial for training robust models.

Computational Efficiency: 3D MRI volumes are computationally intensive, requiring substantial memory and processing power for model training and inference. Developing CNN architectures that balance accuracy with computational efficiency is essential for practical deployment in clinical settings.

Clinical Interpretability: While deep learning models can achieve impressive segmentation performance, understanding the rationale behind their predictions is crucial for clinical acceptance. Ensuring the interpretability of the segmentation results and providing clinicians with actionable insights is essential for effective integration into clinical workflows. Addressing these challenges requires a comprehensive approach that encompasses data pre-processing, model development, training optimization, performance evaluation, and clinical validation. By tackling these issues, the proposed deep learning-based framework aims to provide clinicians with a reliable and efficient tool for brain tumor detection and segmentation from 3D MRI scans, ultimately improving patient care and outcomes in neuroimaging. A robust deep learning-based system capable of accurately segmenting brain tumors from 3D MRI scans in real-time. The system should provide reliable support to healthcare professionals in diagnosing and monitoring brain tumor patients, ultimately improving patient care and treatment outcomes.

Improved Accuracy: Deep learning-based segmentation can provide more accurate and consistent tumor delineation compared to traditional methods, reducing the risk of misdiagnosis.

Time Efficiency: Automation of tumor segmentation speeds up the diagnostic process, allowing healthcare professionals to focus more on treatment planning and patient care.

Personalized Treatment: Precise tumor segmentation enables personalized treatment strategies tailored to each patient's specific condition, leading to better therapeutic outcomes.

CHAPTER 2

LITERATURE REVIEW

1. **TITLE:** MRI Brain Tumor Detection Methods Using Contourlet Transform Based on Time Adaptive Self-Organizing Map
   AUTHOR: Farzamnia, Seyed Hamidreza Hazaveh.

   YEAR: 2023

   The brain is one of the most complex organs in the body, composed of billions of cells that work together to ensure proper functioning. However, when cells divide in a disorderly manner, abnormal growths can occur, forming colonies that can disrupt the normal functioning of the brain and damage healthy cells. Brain tumors can be classified as either benign or low-grade (grade 1and 2), or malignant or high grade (grade 3 and 4). In this article, we propose a nova method that uses contourlet transform and time adaptive self-organizing map, optimized by the whale optimization algorithm, to distinguish between benign and malignant brain tumors in MRI images. Accurate classification of these images is critical for medical diagnosis and treatment. Our method is compared to other methods used in past research and shows promising results for the precise classification of MRI brain images. Through conducting experiments on different test samples, our system has successfully attained a classification accuracy exceeding 98.5%.

2. **TITLE:** Brain Tumor Detection Using 3d-Unet Segmentation Features and Hybrid Machine Learning Model**.**

   AUTHOR: Abid Ishaq, Bhargav Mallam Pati, Furqan Rustam.

   YEAR: 2023

   This study focuses on deploying a machine learning-based approach for brain tumor detection, utilizing Magnetic Resonance Imaging (MRI) features.

We train the proposed model using 3D-UNet and 2D-UNet segmentation features extracted from MRI, encompassing shape, statistics, gray level size zone matrix, gray level dependence matrix, gray level co-occurrence matrix, and gray level run length matrix values. To improve performance, we propose a hybrid model that combines the strengths of two machine learning models, K-nearest neighbor (KNN) and gradient boosting classifier (GBC), using soft voting criteria.

3. **TITLE:** Seresu-Net for Multimodal Brain Tumor Segmentation. **AUTHOR:** Chengdong Y Jurong.

   YEAR: 2022

   Glioma is the most common type of brain tumor, and it has a high mortality rate. Accurate tumor segmentation based on magnetic resonance imaging (MRI) is of great significance for the diagnosis and treatment of brain tumors. Recently, the automatic segmentation of brain tumors based on U-Net has gained considerable attention. Our findings demonstrate that the proposed SERes U-Net has a competitive effect in segmenting multimodal brain tumors.

4. **TITLE:** Improving Effectiveness of Different Deep Transfer Learning- Based Models For Detecting Brain Tumors From MRI Images.

   AUTHOR: Qurrat Ain, Wenhui Yi.

   YEAR: 2020

   Early classification of brain tumors from magnetic resonance imaging (MRI) plays an important role in the diagnosis of such diseases. There are many diagnostic imaging methods used to identify tumors in the brain. MRI is commonly used for such tasks because of its unmatched image quality. This study aimed to develop a robust and efficient method based on transfer learning technique for classifying brain tumors using MRI. The proposed method is superior to the existing literature, indicating that it can be used to classify brain tumors quickly and accurately.

5. **TITLE:** A Deep Learning Model Based on Concatenation Approach For The Diagnosis Of Brain Tumor**.**

AUTHOR: Neelum Noreen, Sellappan Palaniappan.

YEAR: 2020

This study proposes a method of multi-level features extraction and concatenation for early diagnosis of brain tumor. wo different scenarios of brain tumor detection and its classification were evaluated. First, the features from different Inception modules were extracted from pre-trained Inception-v3 model and concatenated these features for brain tumor classification. Then, these features were passed to soft max classifier to classify the brain tumor. As results indicated, the proposed method based on features concatenation using pre-trained models outperformed as compared to existing state-of-the-art deep learning and machine learning based methods for brain tumor classification.

6. **TITLE:** Brain Tumor Classification and Detection Based Dl Models: A Systematic Review.

AUTHOR: Farhan Mohamed Myasar Mundher Adnan, Karrar Neamah.

YEAR: 2022

The realms of computer vision and deep learning have ushered in transformative changes across various domains. Among these, deep learning stands out for its remarkable capacity to handle vast datasets, revolutionizing numerous fields, including the biomedical sector. Its prowess has been harnessed in the realm of brain tumor identification through MRI scans, yielding impressive results. This research project is dedicated to conducting exhaustive exploration of existing endeavors in the domain of brain tumor identification and classification via MRI scans.

7. **TITLE:** Brain Tumor Detection and Classification using Intelligence Techniques.

   AUTHOR: Shubhangi Solanki, Uday Pratap Singh.

   YEAR: 2021

   The main disinterest of this study stays to offer investigators, comprehensive literature on Magnetic Resonance (MR) imaging's ability to identify brain tumors. Using computational intelligence and statistical image processing techniques, this research paper proposed several ways to detect brain cancer and tumors. This paper also explains the morphology of brain tumors, accessible data sets, augmentation methods, component extraction, and categorization among Deep Learning (DL). Finally, our study compiles all relevant material for the identification of understanding tumors, including their benefits, drawbacks, advancements, and upcoming trends.

8. **TITLE:** An Efficient Classification of MRI Brain Images**.**

   AUTHOR: Hira Kanwal, Muhammad Assam.

   YEAR: 2020

   This paper proposes a simple but efficient solution for the classification of MRI brain images into normal, and abnormal images containing disorders and injuries. It uses images with brain tumor, acute stroke and Alzheimer, besides normal images, from the public dataset developed by Harvard medical school, for evaluation purposes. The proposed model is a four-step process, in which the steps are named- Pre-processing, Features Extraction, Features

Reduction, and Classification. Median filter, being one of the best algorithms, is used for the removal of noise such as salt and pepper, and unwanted components such as scalp and skull.

9. **TITLE:** Exploring SMRI Biomarkers for Diagnosis Of Autism Spectrum Disorders Based On Multi Class Activation Mapping Models.

AUTHOR: Fengkai Ke, Rui Yang.

YEAR: 2020

With the continuous development of artificial intelligence, image aided diagnosis of brain diseases has been widely studied and concerned. However, many doctors and researchers still doubt the diagnosis basis of the neural network and think that the neural network belongs to a limited interpretable black-box function approximator. brain tumor identification through MRI scans, yielding impressive results. This research project is dedicated to conducting exhaustive exploration of existing endeavors in the domain of brain tumor identification and classification via MRI scans. They are not sure whether the neural network has learned some interpretive image features like humans. To solve this problem, three new models (2D CAM, 3D CAM and 3D Grad-CAM) are proposed for structural Magnetic Resonance Imaging (s MRI) data. The Regions of Interest (ROI) of subcortical tissues among models and between groups are analyzed based on the heat maps of the three models.

10. TITLE: Brain Tumor and Glioma Grade Classify Using Gaussian Convolutional Neural Network.

AUTHOR: Uday Pratap Singh

YEAR: 2020

Understanding brain diseases such as categorizing Brain-Tumor (BT) is critical to assess the tumors and facilitate the patient with proper cure as per their categorizations. Numerous imaging schemes exist for BT detection, such as Magnetic Resonance Imaging (MRI), generally utilized because of the better quality of images and the reality of depending on non-ionizing radiation. This paper proposes an approach to detect distinctive BT types using Gaussian Convolutional Neural Network (GCNN) on two datasets. One of the datasets is used to classify tumors into pituitary, glioma, and meningioma. The other separates in three grades of glioma, i.e., Grade-two, Grade-three, and Grade-four. In this article, we propose a nova method that uses contourlet transform and time adaptive self-organizing map, optimized by the whale optimization algorithm, to distinguish between benign and malignant brain tumors in MRI images. Accurate classification of these images is critical for medical diagnosis and treatment. Our method is compared to other methods used in past research and shows promising results for the precise classification of MRI brain images.

CHAPTER 3

SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

In the early 2010s, machine learning-based approaches for 3D MRI segmentation in brain tumor detection were gaining traction, although deep learning techniques had not yet reached their current prominence in medical image analysis. During this period, researchers explored various methodologies aimed at automating the segmentation process and improving diagnostic accuracy. One prevalent approach involved the use of feature-based methods, where handcrafted features such as intensity, texture, and shape descriptors were extracted from MRI images. Another strategy employed atlas-based segmentation techniques, where pre- segmented MRI atlases were registered to target MRI scans, and segmentation labels were propagated from the atlas to the target images. While atlas-based methods offered a systematic framework for segmentation, they were hindered by registration inaccuracies and the availability of high-quality atlases. while machine learning-based approaches for 3D MRI segmentation in brain tumor detection in the field was still evolving, and deep learning methods had not yet fully emerged as the dominant paradigm.

3.1.1 DRAWBACKS OF EXISTING SYSTEM

Dependency on Handcrafted Features:

Feature-based methods relied heavily on handcrafted features extracted from MRI images. These features often required expert domain knowledge and manual tuning, making the approach labor intensive and limiting its ability to capture complex spatial relationships within the data.

Difficulty in Handling Variability:

Machine learning-based approaches struggled to handle the inherent variability in MRI data arising from differences in scanner settings, patient demographics, and imaging protocols. This variability could lead to reduced segmentation accuracy and generalization performance across diverse datasets.

Limited Integration of Contextual Information:

Traditional machine learning methods often lacked the ability to effectively capture contextual information and spatial dependencies within volumetric MRI data. As a result, segmentation accuracy may have been compromised, particularly in regions with complex anatomical structures or pathologies.

Computational Intensity of Patch-Based Techniques:

Patch-based methods divided MRI volumes into smaller patches for processing, resulting in increased computational complexity, especially for large datasets. Additionally, the performance of patch-based methods was sensitive to patch size and overlap parameters, requiring careful optimization.

3.2 PROPOSED SYSTEM

The proposed system aims to leverage the power of deep learning, specifically Convolutional Neural Networks (CNNs), for accurate and efficient segmentation of brain tumors from 3D MRI scans. Building upon the limitations of existing machine learning-based approaches, the proposed system seeks to overcome challenges and enhance segmentation performance through the following key components and methodologies.

CNN Architecture Design:

Develop a CNN architecture tailored for 3D MRI segmentation that can effectively capture spatial dependencies and hierarchical features within volumetric medical images. This architecture should be designed to balance between model complexity and computational efficiency while ensuring robust segmentation performance.

Data Pre-processing:

It is very difficult to process an image. Before any image is processed, it is very significant to remove unnecessary items it may hold. After removing unnecessary artifacts, the image can be processed successfully. The initial step of image processing is Image Pre-Processing. Preprocessing involves processes like conversion to grayscale image, noise removal and image reconstruction. Conversion to grey scale image is the most common pre- processing practice. After the image is converted to grayscale, then remove excess noise using different filtering methods.

Feature extraction:

Feature extraction is an important step in the construction of any pattern classification and aims at the extraction of the relevant information that characterizes each class. In this process relevant features are extracted from objects/ alphabets to form feature vectors. These feature vectors are then used by classifiers to recognize the input unit with target output unit. It becomes easier for the classifier to classify between different classes by looking at these features as it allows easy to distinguish. Feature extraction is the process to retrieve the most important data from the raw data.

Multimodal Fusion.

Segmentation of images is important as large numbers of images are generated during the scan and it is unlikely for clinical experts to manually divide these images in reasonable time. Image segmentation refers to segregation of given image into multiple non-overlapping regions.

Segmentation represents the image into sets of pixels that are more significant and easier for analysis. It is applied to approximately locate the boundaries or objects in an image and the resulting segments collectively cover the complete image. The segmentation algorithms work on one of the two basic characteristics of image intensity: similarity and discontinuity.

Training Strategy:

Classification is used to classify each item in a set of data into one of predefined set of classes or groups. In other words, classification is an important technique used widely to differentiate normal and tumor brain images. The data analysis task classification is where a model or classifier is constructed to predict categorical labels (the class label attributes). Classification is a data mining function that assigns items in a collection to target categories or classes. The goal of classification is to accurately predict the target class for each case in the data.

3.2.1 ADVANTAGES OF PROPOSED SYSTEM

Combining multiple imaging modalities enhances accuracy by providing complementary information. improving the system's ability to differentiate between tumor and normal tissue. Enhances robustness-As the model can adapt to variations in image quality and characteristics across different modalities. The incorporation of such diverse data sources can improve sensitivity and specificity, leading to more reliable and precise tumor identification in clinical settings. We can be able to predict the brain tumor grade, size, and the location and by giving suggestions we can able to treat the tumor with the most care.

High Accuracy: CNNs excel at capturing intricate patterns and features within volumetric MRI data, leading to higher segmentation accuracy compared to traditional methods. Their ability to learn hierarchical representations from raw data allows for more precise delineation of tumor boundaries.

Generalization: CNNs trained on large-scale datasets can generalize well to diverse patient populations and imaging conditions. They can adapt to variations in MRI protocols, scanner types, and patient demographics, resulting in robust segmentation performance across different datasets.

Scalability: Deep learning-based segmentation using CNNs can be easily scaled to handle large datasets and complex imaging tasks. With advances in hardware acceleration and parallel computing, CNN models can process 3D MRI volumes efficiently, making them suitable for real-time applications and high-throughput analysis.

Adaptability: CNN architectures can be adapted and optimized for specific segmentation tasks, including different types of brain tumors and imaging modalities. This flexibility allows researchers and clinicians to tailor the segmentation model to meet specific clinical needs and challenges.

3.3 FEASIBILITY STUDY

In a feasibility study for 3D MRI segmentation aimed at detecting brain tumors, several key components need evaluation. Firstly, the existing technology landscape should be assessed, including the availability of high-resolution MRI scanners and advanced computing hardware for processing volumetric data efficiently. Secondly, the accuracy and reliability of segmentation algorithms, such as convolutional neural networks (CNNs) or deep learning approaches, must be investigated, considering their ability to differentiate tumor tissue from healthy brain structures. Moreover, computational resources required for real-time or near-real-time segmentation should be analyzed to ensure practical implementation in clinical settings. Additionally, the compatibility of segmentation techniques with existing MRI protocols and medical imaging software needs consideration for seamless integration into healthcare workflows. Furthermore, the potential clinical impact and utility of accurate tumor segmentation in diagnosis, treatment planning, and monitoring of brain tumors should be explored, including its ability to provide quantitative biomarkers for disease progression assessment. Addressing regulatory and ethical considerations, such as patient data privacy and regulatory approvals for medical device usage, is vital for ensuring compliance with healthcare standards and guidelines.

3.3.1 ECONOMIC FEASIBILITY

Economic feasibility for implementing 3D MRI segmentation for brain tumor detection involves assessing costs versus benefits. Factors include equipment costs, software licenses, personnel training, and potential savings from improved accuracy and efficiency in diagnosis and treatment planning. Additionally, consider the potential for reduced healthcare costs through early detection and intervention.

3.3.2 TECHNICAL FEASIBILITY

Brain tumor detection through 3D MRI segmentation involves advanced image processing techniques. MRI (Magnetic Resonance Imaging) provides detailed images of the brain's internal structures, making it an essential tool for diagnosing tumors. Segmentation, the process of partitioning an image into meaningful regions, is crucial for isolating the tumor from surrounding tissues. Various segmentation algorithms are employed, including thresholding, region growing, and machine learning-based methods like convolutional neural networks (CNNs). CNNs have shown remarkable performance in segmenting brain tumors from MRI scans.

3.3.3 SOCIAL FEASIBILITY

Implementing 3D MRI segmentation for detecting brain tumors can significantly enhance medical diagnostics and patient outcomes. However, its social feasibility hinges on various factors that warrant careful consideration. Accessibility to MRI technology is a primary concern. While developed regions may have widespread access to MRI machines, rural or poor areas may face barriers in acquiring and maintaining such advanced equipment. Addressing these disparities is essential to ensure equitable healthcare access for all demographics.

CHAPTER 4

SYSTEM DESIGN

4.1 SYSTEM ARCHITECTURE

A system architecture is a representation of a system in which there is a mapping of functionality onto hardware and software components, a mapping of the software architecture onto the hardware architecture, and human interaction with these components.

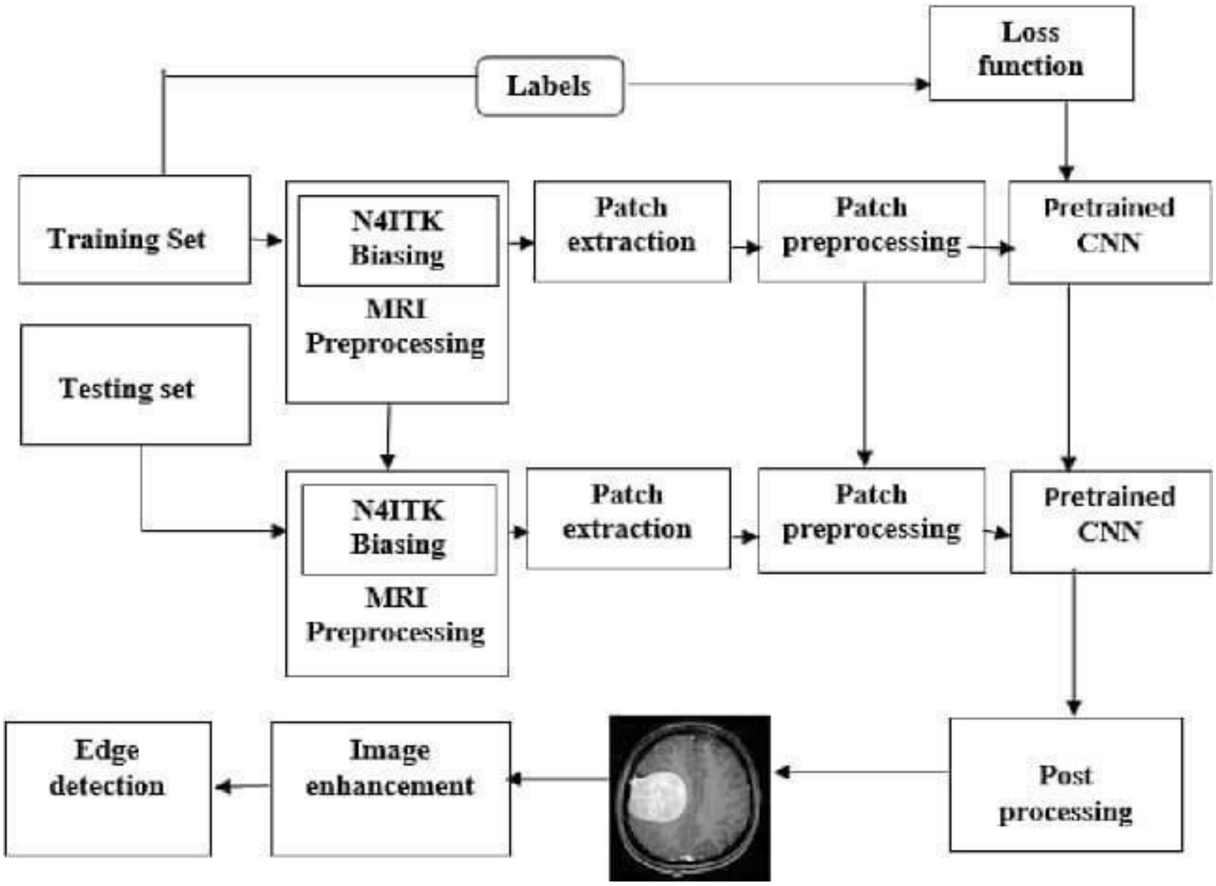


Fig 4.1 System Architecture

4.2 UML DIAGRAM

4.2.1 USECASE DIAGRAM

UML stands for Unified Modelling Language. UML is a standardized general- purpose modelling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group. The goal is for UML to become a common language for creating models of object-oriented computer software. In its current form UML is comprised of two major components: a Meta- model and a notation. In the future, some form of method or process may also be added to; or associated with, UML. The Unified Modelling Language is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software system, as well as for business modelling and other non-software systems.

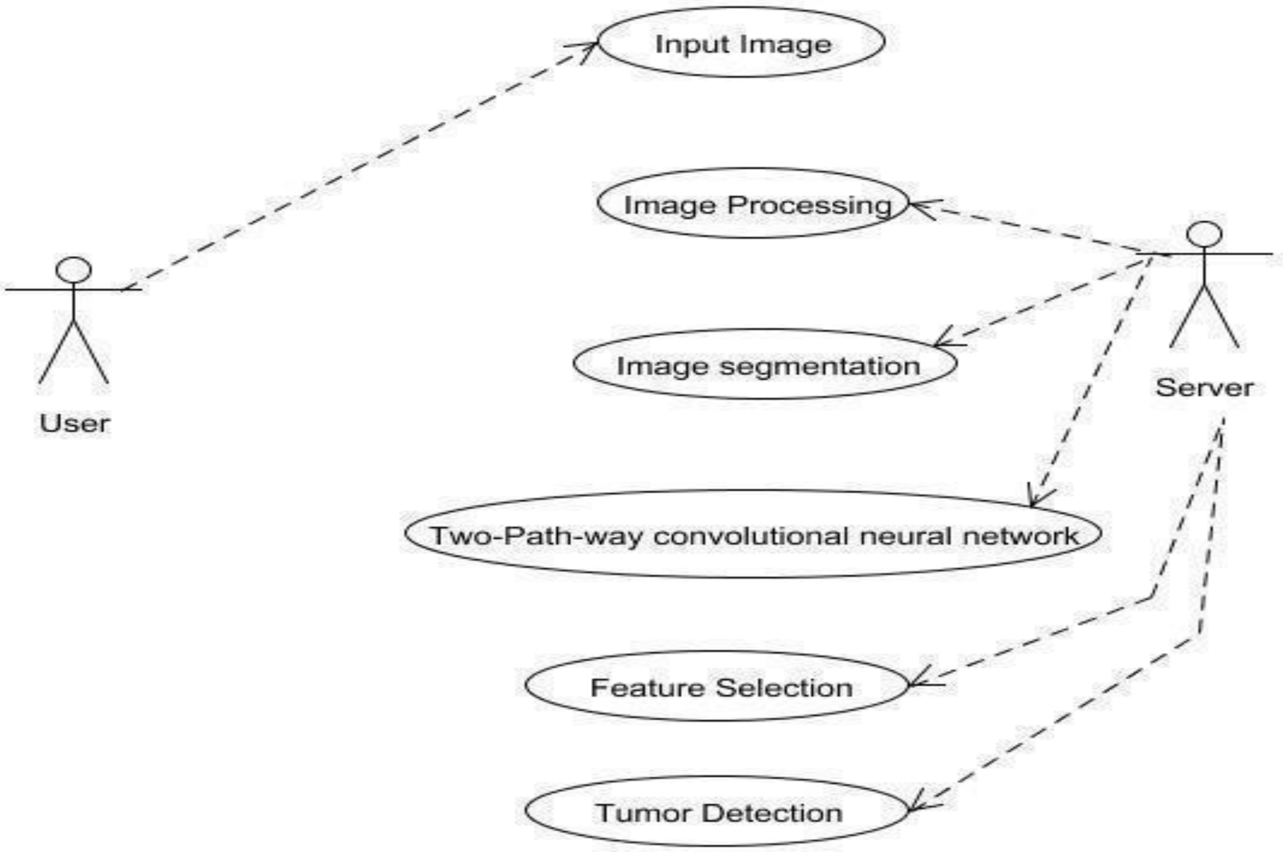


Fig 4.2 Use Case Diagram

4.2.2 COLLABORATION DIAGRAM:

UML collaboration diagram illustrates the relationship and interaction between software objects. They assume that use cases, system usage contracts and domain models already exist. The collaboration diagram shows the messages sent between the class and the object.

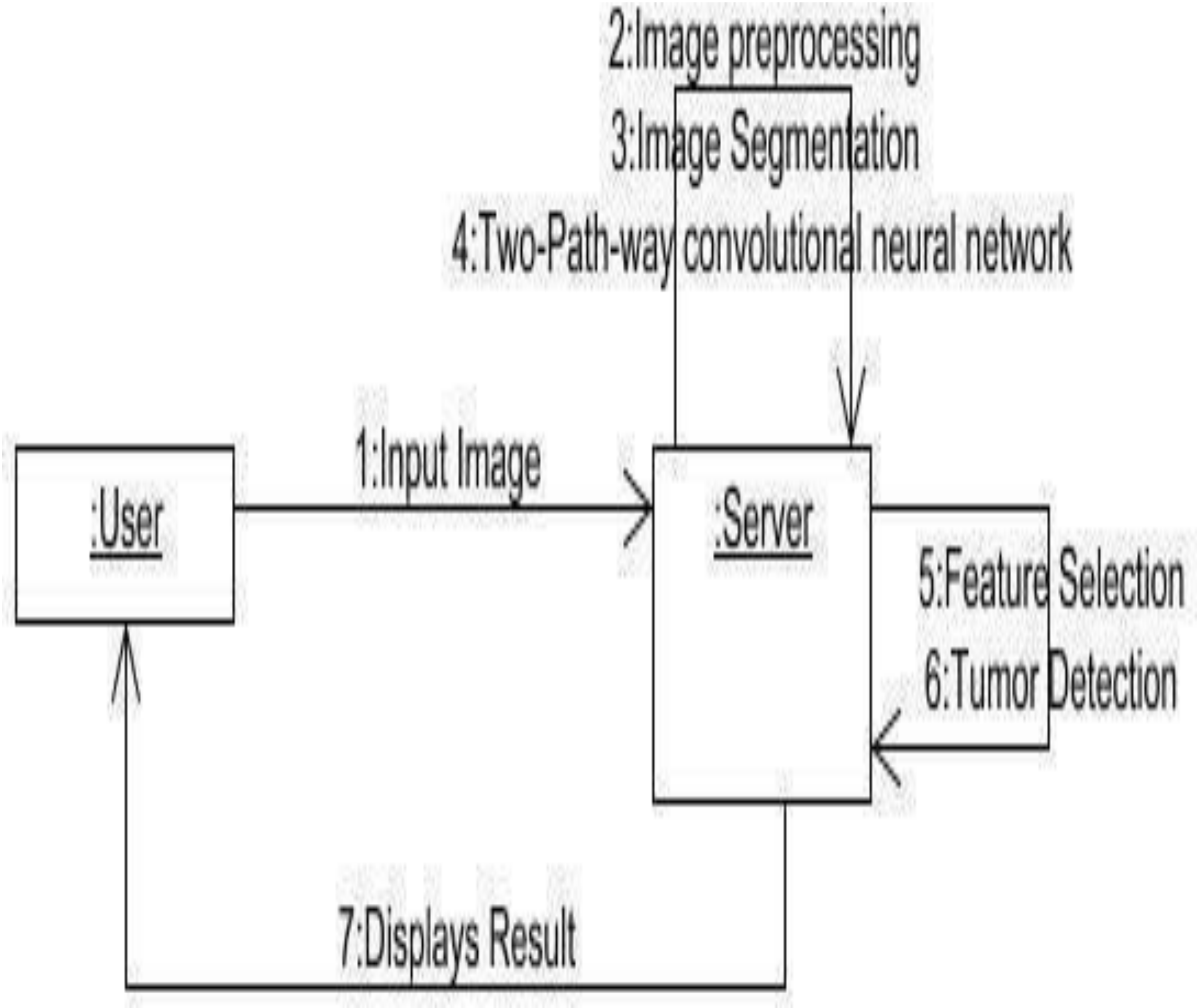


Fig 4.3 Collaborative Diagram

4.2.3 ACTIVITY DIAGRAM

Activity diagram is a graphical representation of workflows of stepwise activities and actions with support for choice, iteration, and concurrency. An activity diagram shows the overall flow of control.

The most important shape types:

- Rounded rectangles represent activities.
- Diamonds represent decisions.
- Bars represent the start or end of concurrent activities.
- A black circle represents the start of the workflow.
- An encircled circle represents the end of the workflow.

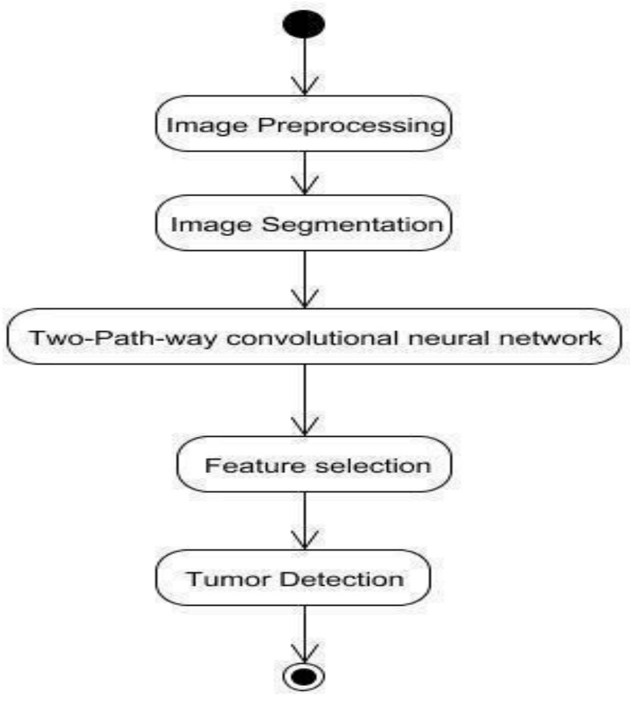


Fig 4.4 Activity Diagram

4.2.4 SEQUENCE DIAGRAM

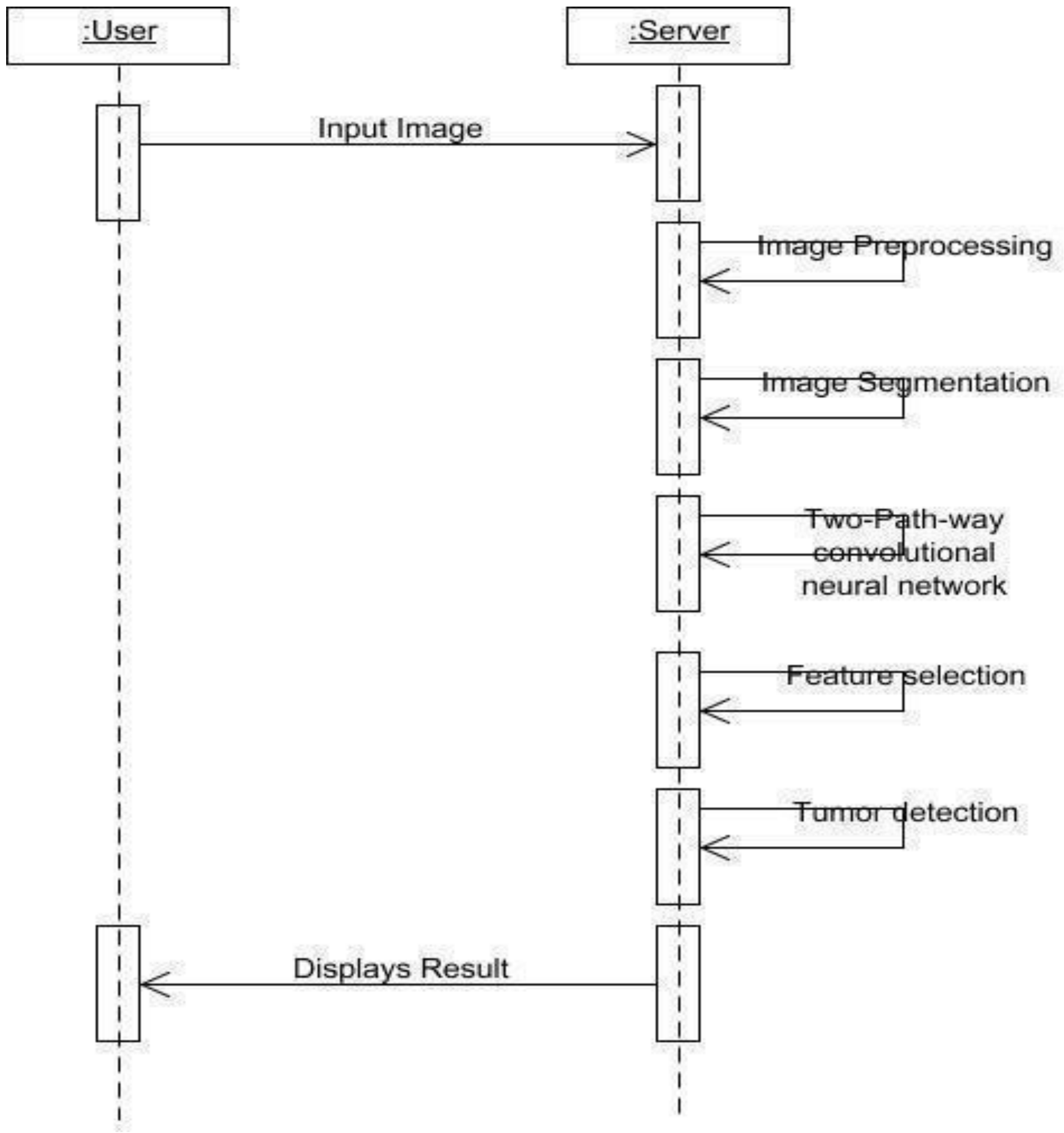
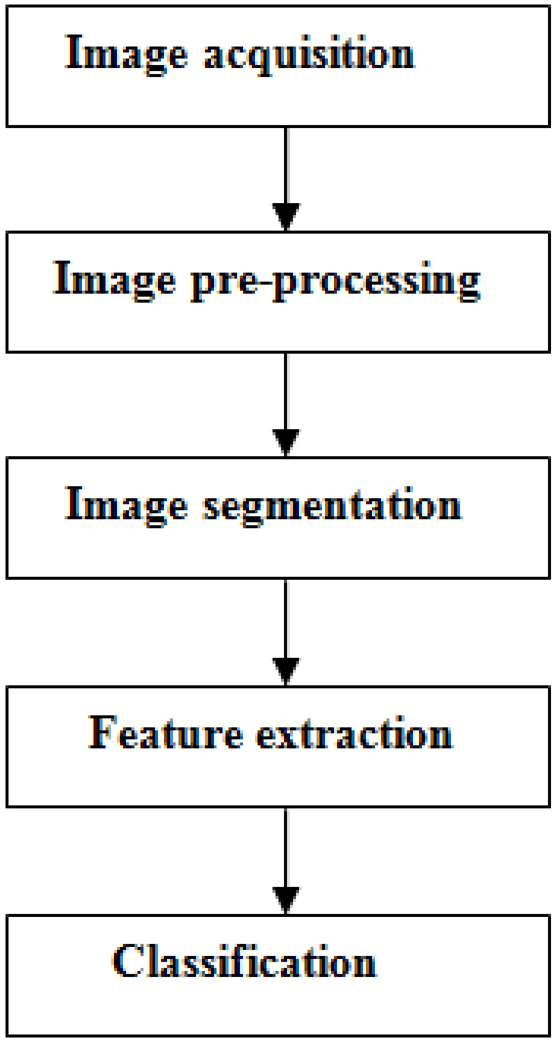


Fig 4.5 Sequence Diagram

4.3 DATA FLOW DIAGRAM

LEVEL-0



LEVEL-1

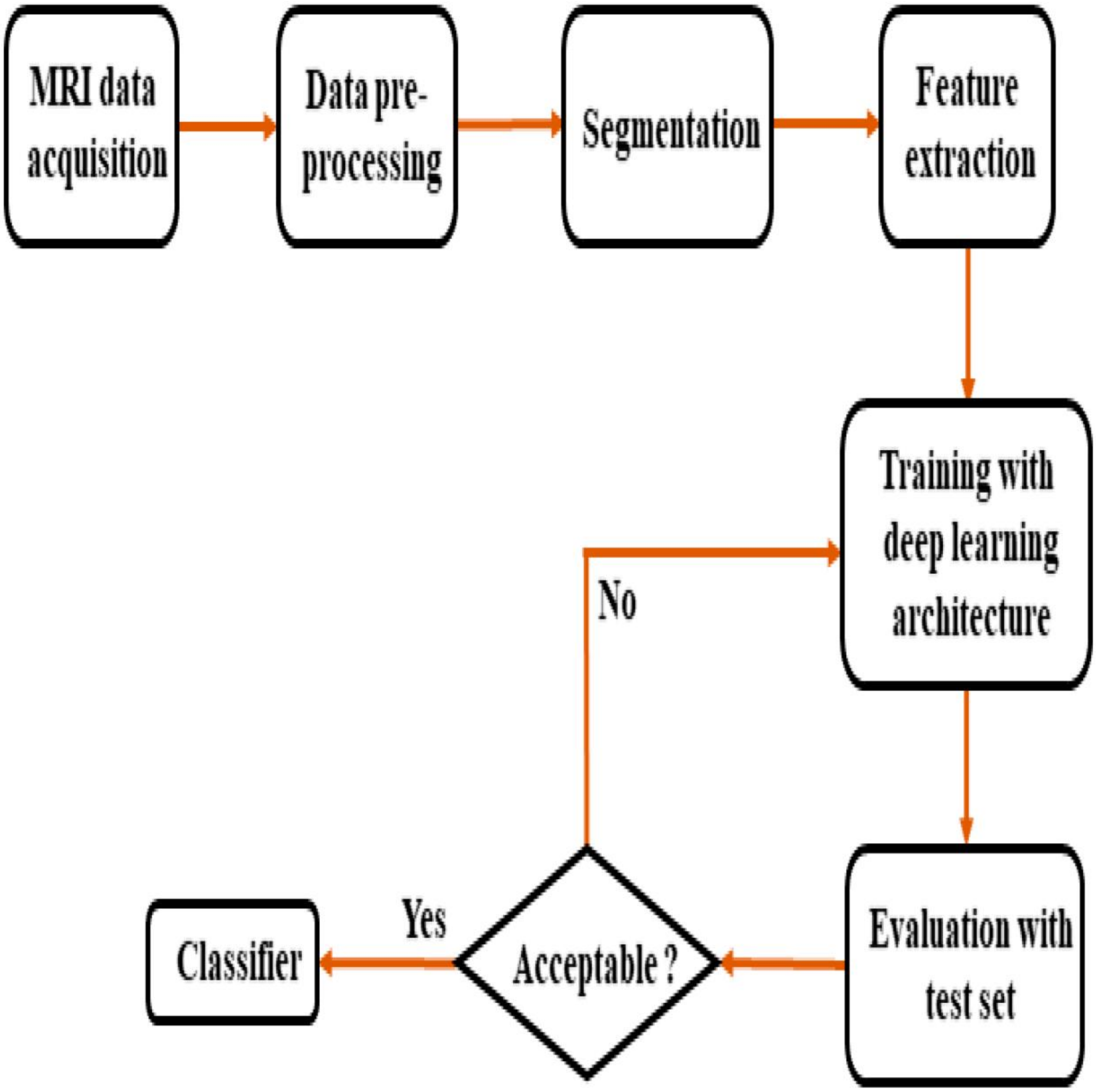


Fig 4.6 Data flow Diagram

CHAPTER 5

SYSTEM REQUIREMENTS

5.1 SYSTEM REQUIREMENT

5.1.1 HARDWARE REQUIREMENT

- Processor intel core i3
- RAM 4.00 GB
- Hard Disk 1Tb

5.1.2 SOFTWARE REQUIREMENTS

- Windows 10
- Python
- Deep learning Frameworks
- Image processing libraries
- Open-CV

CHAPTER 6

SYSTEM IMPLEMENTATION

6.1 INTRODUCTION TO PYTHON:

PYTHON LANGUAGE: Python is an object-oriented programming language created by Guido Rossum in 1989. It is ideally designed for rapid prototyping of complex applications. It has interfaces to many OS system calls and libraries and is extensible to C or C++. Many large companies use the Python programming language include NASA, Google, YouTube, BitTorrent, etc. Python programming is widely used in Artificial Intelligence, Natural Language Generation, Neural Networks, and other Advanced fields of Computer Science. Python had deep focus on code readability & this class will teach you python from basics.

PYTHON PROGRAMMING CHARACTERISTICS

- It provides rich data types and easier to read syntax than any other programming languages.
- It is a platform independent scripted language with full access to operating system API's.
- Compared to other programming languages, it allows more run-time flexibility.
- It includes the basic text manipulation facilities of Perl and Awk.
- A module in Python may have one or more classes and free functions.
- Libraries in Pythons are cross-platform compatible with Linux, Macintosh, and Windows.

6.2 IMAGE PROCESSING TOOLBOX

MATLAB, short for "Matrix Laboratory," is a high-level programming language and interactive environment primarily designed for numerical computation, data analysis, and visualization. It allows users to perform a wide range of tasks, including mathematical calculations, algorithm development, data analysis, and graphical plotting, all within a single environment.

Here are some key features and capabilities of MATLAB:

Matrix Operations: MATLAB's core strength lies in its ability to efficiently handle matrix operations. It provides built-in functions for matrix manipulation, linear algebra, and numerical computations.

Programming Environment: MATLAB offers an interactive programming environment with a command-line interface, allowing users to execute commands and scripts in real-time. It also supports the development of custom functions and scripts using a high-level programming language that resembles natural mathematical notation.

Data Visualization: MATLAB provides powerful tools for creating 2D and 3D plots, histograms, scatter plots, and other graphical representations of data. Its plotting functions allow users to customize various aspects of the visualization, such as colors, line styles, and annotations.

6.3 CONVOLUTIONAL NEURAL NETWORK

A Convolutional Neural Network (Conv-Net/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a Conv-Net is much lower as compared to other classification algorithms. While in primitive methods filters are hand engineered, with enough training, Conv-Nets can learn these filters/characteristics. The architecture of a Conv-Net is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlaps to cd over the entire visual area. The objective of the Convolution Operation is to extract the high-level features such as edges, from the input image. Conv-Nets need not be limited to only one Convolutional Layer. Conventionally, the first Cavalier is responsible for capturing the Low-Level features such as edges, color, gradient orientation, etc. With added layers, the architecture adapts to the High-Level features as well, giving us a network, which has the wholesome understanding of images in the dataset, like how we would.

6.4 MAGNETIC RESONANCE IMAGING (MRI)

The MRI is a diagnostic tool used for analyzing and studying the human anatomy. The medical images acquired in various bands of the electromagnetic spectrum. The wide variety of sensors used for the acquisition of images and the physics behind them, make each modality suitable for a specific purpose. In MRI, the pictures are produced using a magnetic field, which is approximately 10,000 times stronger than the earth's magnetic field. The MRI produces more detailed images than other techniques, such as CT or ultrasound. The MRI also provides maps of anatomical structures with a high soft-tissue contrast.

Basically, the magnetic resonance of hydrogen (1H) nuclei in water and lipid is measured by an MRI. scanner. As the signal values are 12-bit coded, 4096 shades can be represented by a pixel. The MRI scanners require a magnetic field, and it is available at 1.5 or 3 T. In comparison with the earth's magnetic field (~50 ft.) the magnetic field of a 3 T MRI scanner is approximately 60,000 times the earth field. The patient is placed in a strong magnetic field, which causes the protons in the water molecules of the body to align either in a parallel or anti-parallel orientation with the magnetic field. A radiofrequency pulse is introduced, causing the spinning protons to move out of the alignment. When the pulse is stopped, the protons realign and emit radio frequency energy signal that is localized by the magnetic fields and are spatially varied and rapidly turned on and off. A radio antenna within the scanner detects the signal and creates the image. Functional MRI is a technique for examining the brain activation, which unlike PET, is non-invasive with relatively high spatial resolution.

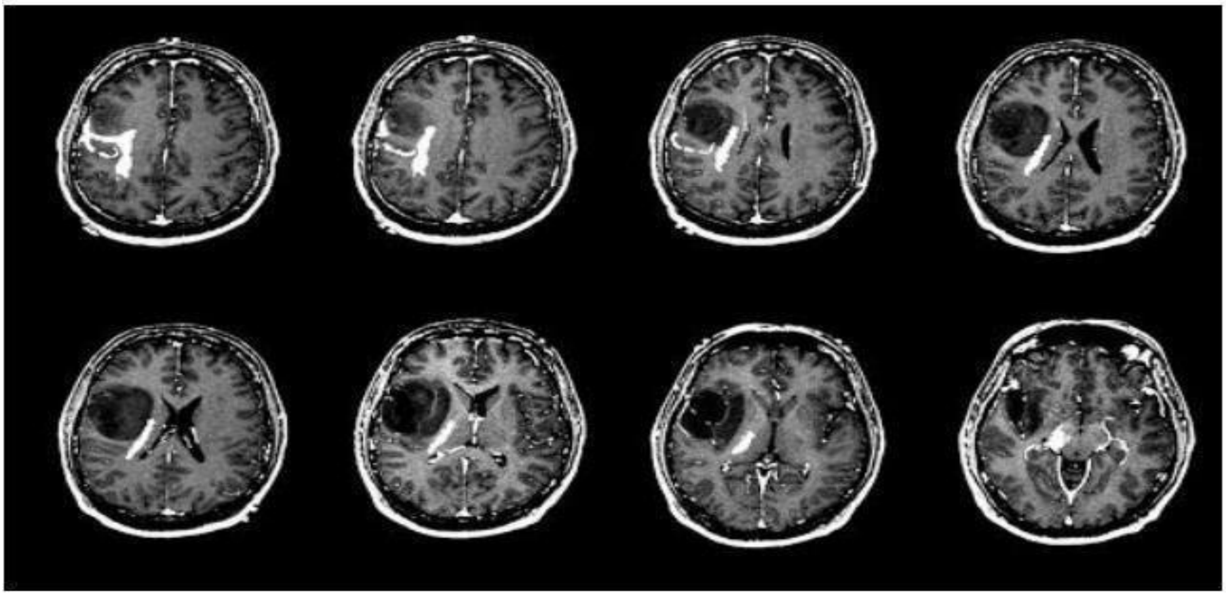


Figure 4.6 MRI of Human Brain

The most common method utilizes a technique called blood oxygen level dependent contrast. This is an example of endogenous contrast, making use of the inherent signal differences in blood oxygenation content. In the normal resting state, a high concentration of deoxyhemoglobin attenuates the MRI signal due to its paramagnetic nature. However, the neuronal activity, in response to some task or stimulus, creates a local demand for the oxygen supply, which increases the fraction of oxy hemoglobin causing a signal increase on T2 or T2*-weighted images. In a typical experiment, the patient is subjected to a series of rest and task intervals, during which MRI images are repeatedly acquired. A radio antenna within the scanner detects the signal and creates the image. Functional MRI is a technique for examining the brain activation, which unlike PET, is non-invasive with relatively high spatial resolution. The signal changes during time are then examined on a pixel by-pixel basis to test how well they correlate with the known stimulus pattern. The pixels that demonstrate a statistically significant correlation are highlighted in color and overlaid onto a grayscale MRI image to create an activation map of the brain. The location and extent of activation is linked to the type of stimulus. Thus, a simple thumb finger movement task will produce activation in the primary motor cortex.

6.5 MODULE DESCRIPTION:

Those are the modules of the project.

- Data Preprocessing.
- Feature Extraction.
- Multimodal fusion.
- Training Strategy.

Data Preprocessing.

In the realm of medical imaging, particularly in the detection and segmentation of brain tumors using 3D MRI scans, data preprocessing is paramount for ensuring the reliability and accuracy of subsequent deep learning algorithms, particularly Convolutional Neural Networks (CNNs). model becomes less sensitive to these variations, enhancing its robustness.

Moreover, noise reduction techniques are applied to mitigate the effects of noise present in MRI images, which could otherwise compromise segmentation accuracy. Techniques such as Gaussian filtering or median filtering are commonly employed to achieve this. Additionally, skull stripping methods are utilized to remove non-brain tissues from the scans, focusing the model's attention exclusively on the relevant brain regions.

In the supervised learning paradigm, accurate labeling of MRI scans is essential. Ground truth labels, indicating tumor regions, are meticulously generated, or provided, ensuring alignment with the corresponding MRI images. Data splitting is then performed to partition the dataset into training, validation, and testing sets, allowing for the evaluation of the model's performance on unseen data. Finally, a robust data loading and preprocessing pipeline is constructed to efficiently handle large volumes of MRI data, applying the preprocessing steps seamlessly. By meticulously preparing the data in this manner, the subsequent CNN algorithm can effectively learn discriminative features for accurate brain tumor segmentation. This, in turn, holds immense promise for enhancing diagnostic capabilities and ultimately improving patient outcomes in the field of neuroimaging.

Feature Extraction

In the vast realm of artificial intelligence and machine learning, the quest for innovation and advancement knows no bounds. From natural language processing to computer vision, from reinforcement learning to robotics, the field continues to evolve at an unprecedented pace, fueled by a combination of theoretical breakthroughs, algorithmic innovations, and the ever-expanding availability of data. Deep learning has emerged as a transformative force, revolutionizing how we tackle complex problems across various domains. Its ability to automatically learn intricate patterns and representations from raw data has led to remarkable breakthroughs in tasks such as image recognition, speech synthesis, medical diagnosis, and autonomous driving. With the proliferation of deep learning frameworks and the democratization of AI tools, researchers, engineers, and enthusiasts worldwide are empowered to explore new frontiers and push the boundaries of what is possible. However, amidst the excitement and optimism, challenges and ethical considerations loom large. Concerns regarding data privacy, algorithmic bias, and the societal impact of AI applications underscore the need for responsible development and deployment of AI technologies. As we navigate this rapidly evolving landscape, collaboration, transparency, and interdisciplinary approaches are key to harnessing the full potential of AI for the betterment of humanity. Through concerted efforts and collective wisdom, we can steer AI towards a future where innovation serves as a force for good, empowering individuals, enriching communities, and fostering a more equitable and sustainable world.

Multimodal fusion

Multimodal fusion 3D MRI segmentation represents a cutting-edge approach in medical imaging, particularly in the realm of brain tumor detection. Leveraging Convolutional Neural Network (CNN) algorithms powered by deep learning, this methodology aims to revolutionize the accuracy and efficiency of tumor identification within MRI scans. The integration of multiple imaging modalities, such as T1-weighted, T2-weighted, and FLAIR (Fluid Attenuated Inversion Recovery), allows for a comprehensive analysis of the brain tissue, enabling the detection of subtle abnormalities that may indicate the presence of a tumor.

The CNN-based deep learning models employed in this technique are trained on vast datasets of annotated MRI scans, enabling them to learn complex patterns and features indicative of tumor presence In clinical practice, multimodal fusion 3D MRI segmentation holds tremendous promise for enhancing the accuracy and efficiency of brain tumor diagnosis. By providing radiologists and clinicians with detailed and precise information about tumor location, size, and characteristics, this approach enables more informed treatment decisions and better patient outcomes.

However, despite its considerable potential, challenges remain in the widespread adoption of this technology. Issues such as data variability, limited interpretability of deep learning models, and the need for robust validation frameworks must be addressed to ensure the reliability and generalizability of segmentation results. In conclusion, multimodal fusion 3D MRI segmentation powered by CNN algorithms represents a significant advancement in brain tumor detection and characterization. By integrating information from multiple imaging modalities and leveraging the capabilities of deep learning, this approach offers unparalleled accuracy and efficiency in identifying tumors within MRI scans.

Training Strategy

Detecting brain tumors through MRI segmentation using Convolutional Neural Networks (CNN) via deep learning represents a cutting-edge approach in medical imaging analysis. The training strategy for such a task encompasses several crucial components aimed at ensuring both accuracy and efficiency in tumor detection. Initially, a robust dataset comprising a diverse range of MRI scans depicting varying tumor types, sizes, and locations is essential.

Pre-processing steps are integral to enhancing the quality of the data and facilitating optimal model performance. Training the CNN involves iteratively optimizing its parameters to minimize the discrepancy between predicted segmentations and ground truth annotations. This optimization process, often performed using stochastic gradient descent or its variants, is guided by a loss function that quantifies the dissimilarity between predicted and true segmentation masks

In conclusion, an effective training strategy for 3D MRI segmentation in brain tumor detection using CNN algorithms encompasses meticulous data preparation, thoughtful model architecture design, iterative optimization, and rigorous validation. By leveraging the power of deep learning and cutting-edge techniques, such as those outlined above, researchers and clinicians can advance the field of medical imaging analysis and contribute to more accurate and timely diagnosis and treatment of brain tumors.

CHAPTER 7

SYSTEM TESTING

Testing is performed to identify errors. It is used for quality assurance. Testing is an integral part of the entire development and maintenance process. The goal of the testing during phase is to verify that the specification has been accurately and completely incorporated into the design, as well as to ensure the correctness of the design itself. For example, the design must not have any logic faults in the design is detected before coding commences, otherwise the cost of fixing the faults will be considerably higher as reflected. Detection of design faults can be achieved by means of inspection as well as walkthrough.

Testing is one of the important steps in the software development phase. Testing checks for the errors, of the project testing involves the following test cases:

- Static analysis is used to investigate the structural properties of the Source code.
- Dynamic testing is used to investigate the behavior of the source code by executing the program on the test data.

7.1 TEST DATA AND OUTPUT UNIT TESTING

Unit testing is conducted to verify the functional performance of each modular component of the software. Unit testing focuses on the smallest unit of the software design (i.e.), the module. The white box testing techniques were heavily employed for unit testing.

7.2 FUNCTIONAL TESTS

Functional test cases involved exercising the code with nominal, input values for which the expected results are known, as well as boundary values and special values, such as logically related inputs, files of identical elements, and empty files.

MRI sequence	V_Loss	V_Acc	Spe	Sen	DSC
FLAIR	0.061	98.95	99.14	98.53	91.23
T1	**0.037**	**99.41**	**99.68**	**98.97**	**93.86**
T1ce	0.072	98.68	98.52	98.72	85.67
T2	0.08	98.25	98.37	98.49	79.32

Three types of tests in Functional test:

- Performance Test
- Stress Test
- Structure Test

PERFORMANCE TEST:

It determines the amount of execution time spent in various parts of the unit, program throughput, and response time and device utilization by the program unit.

STRESS TEST

Stress Test is those tests designed to intentionally break the unit. A Great deal can be learned about the strength and limitations of a program by examining the way a programmer in which a program unit breaks.

STRUCTURED TEST

Structure Tests are concerned with exercising the internal logic of a program and traversing execution paths. The way in which Whitebox test strategy was employed to ensure that the test cases could Guarantee that all independent paths within a module have been exercised at least once.

- Exercise all logical decisions on their true or false sides.
- Execute all loops at their boundaries and within their operational bounds.
- Exercise internal data structures to assure their validity.
- Checking attributes for their correctness.
- Handling end of file condition, I/O errors, buffer problems and textual errors in output information

Integration testing is a systematic technique for construction the program structure while at the same time conducting tests to uncover errors associated with interfacing. i.e., integration testing is the complete testing of the set of modules which makes up the product. The objective is to take untested modules and build a program structure tester should identify critical modules. Critical modules should be tested as early as possible. One approach is to wait until all the units have passed testing, and then combine them and then tested. This approach is evolved from unstructured testing of small programs. Another strategy is to construct the product in increments of tested units. A small set of modules are integrated together and tested, to which another module is added and tested in combination. And so on. The advantages of this approach are that interface dispenses can be easily found and corrected.

The major error that was faced during the project is linking error. When all the modules are combined the link is not set properly with all support files. Then we checked out for interconnection and the links. Errors are localized to the new module and its intercommunications. The product development can be staged, and modules integrated in as they complete unit testing.

Testing is completed when the last module is integrated and tested.

Experimentations with various batch sizes

No.	Batch size	DSC (%)	Findings
1	16	93.17	Near highest performance
2	32	93.86	Highest performance
3	64	93.62	Near highest performance
4	128	92.84	Performance fallen

Experimentations with various number of epochs

No.	Epochs	DSC (%)	Findings
1	50	93.86	Highest performance
2	100	93.86	Highest performance
3	150	93.86	Highest performance

Experimentations with various loss functions

No.	Loss Function	DSC (%)	Findings
1	Categorical Cross-entropy	93.86	Highest performance
2	Binary Cross-entropy	93.86	Highest performance

Experimentations with various optimizers

No.	Optimizer	DSC (%)	Findings
1	Adam	93.86	Highest performance
2	Nadam	93.72	Near highest performance
3	Adamax	93.36	Near highest performance
4	SGD	92.43	Performance fallen

CHAPTER 8

RESULTS AND DISCUSSION

Our data set contains tumor and non-tumor MRI images obtained from various online sources. Use convolutional neural network for detection. Modeling is done using Python language. Calculate the accuracy and compare it with all other modern methods.

To determine the effectiveness of the proposed brain, training accuracy, verification accuracy, and verification loss need to be calculated. Tumor classification scheme. The current technology for detecting brain tumors uses SVM (Support Vector Machine) classification. Feature extraction requires output. Based on the feature value, the classification output is generated, and the accuracy is calculated. Tumor and non-tumor detection based on support vector machines take a long time and have poor calculation accuracy. The proposed CNN-based classification does not require a separate feature extraction step. The value of this function is taken from CNN itself. In the picture. The classification results of tumor and non-tumor brain imaging are shown. Therefore, the complexity and calculation time are low and accurate. The figure shows the results of brain tumor classification accuracy. Finally, according to the value of the probability score, it is classified as brain tumor or non- tumor brain. Normal brain imaging is the least likely. The score value compared with normal and neoplastic brains.

CHAPTER 9

CONCLUSION AND FUTURE ENHANCEMENT

CONCLUSION:

Our data set includes tumor MRI images and non-tumor images obtained from various online sources. Radiation podia contains real patient cases. Tumor images are obtained from the test data set of "Radio podia and Brain Tumor Image Segmentation Benchmark (BRATS) 2015". The detection is carried out through a convolutional network. Modeling is done using Python language. Calculate the accuracy and compare it with all other modern methods. To determine the effectiveness of the proposed brain, training accuracy, verification accuracy, and verification loss need to be calculated.

FUTURE ENHANCEMENT:

Tumor classification scheme. The current technology for detecting brain tumors uses SVM (Support Vector Machine) classification. Feature extraction requires output. Based on the feature value, the classification output is generated, and the accuracy is calculated. Tumor and non-tumor detection based on support vector machines take a long time and have poor calculation accuracy. The proposed CNN-based classification does not require a separate feature extraction step. The value of this function is taken from CNN itself. In the picture. The classification results of tumor and non-tumor brain imaging are shown. Therefore, the complexity and calculation time are low and accurate. The figure shows the results of brain tumor classification accuracy. Finally, according to the value of the probability score, it is classified as brain tumor or non-tumor brain. Normal brain imaging is the least likely. The score value compared with normal and neoplastic brains.

APPENDICES

SOURCE CODE

```
import tkinter
from PIL import Image
from tkinter import filedialog
import cv2 as cv
from frames import *
from displayTumor import *
from predictTumor import *
class Gui:
MainWindow = 0
listOfWinFrame = list()
FirstFrame = object()
val = 0
fileName = 0
DT = object()
wHeight = 700
wWidth = 1180
def __init__(self):
global MainWindow
MainWindow = tkinter.Tk()
MainWindow.geometry('1200x720')
MainWindow.resizable(width=False, height=False)
self.DT = DisplayTumor()
self.fileName = tkinter.StringVar()
self.FirstFrame = Frames(self, MainWindow, self.wWidth, self.wHeight, 0, 0)
```

```
self.FirstFrame.btnView['state'] = 'disable'

self.listOfWinFrame.append(self.FirstFrame)

WindowLabel = tkinter.Label(self.FirstFrame.getFrames(), text="Brain Tumor
Detection", height=1, width=40)

WindowLabel.place(x=320, y=30)

WindowLabel.configure(background="White", font=("Comic Sans MS", 16,
"bold"))

self.val = tkinter.IntVar()

RB1 = tkinter.Radiobutton(self.FirstFrame.getFrames(), text="Detect Tumor",
variable=self.val,value=1, command=self.check)

RB1.place(x=250, y=200)

RB2 = tkinter.Radiobutton(self.FirstFrame.getFrames(), text="View Tumor
Region",

variable=self.val, value=2, command=self.check)

RB2.place(x=250, y=250)

browseBtn = tkinter.Button(self.FirstFrame.getFrames(), text="Browse", width=8,
command=self.browseWindow)

browseBtn.place(x=800, y=550)

MainWindow.mainloop()

def getListOfWinFrame(self):

return self.listOfWinFrame

def browseWindow(self):

global mriImage

FILEOPENOPTIONS = dict(defaultextension='*.*',

filetypes=[('jpg', '*.jpg'), ('png', '*.png'), ('jpeg', '*.jpeg'), ('All Files', '*.*')])

self.fileName = filedialog.askopenfilename(**FILEOPENOPTIONS)

image = Image.open(self.fileName)

imageName = str(self.fileName)

mriImage = cv.imread(imageName, 1)
```

```
self.listOfWinFrame[0].readImage(image)

self.listOfWinFrame[0].displayImage()

self.DT.readImage(image)

def check(self):

global mriImage

#print(mriImage)

if (self.val.get() == 1):

self.listOfWinFrame = 0

self.listOfWinFrame = list()

self.listOfWinFrame.append(self.FirstFrame)

self.listOfWinFrame[0].setCallObject(self.DT)

res = predictTumor(mriImage)

if res > 0.5:

resLabel = tkinter.Label(self.FirstFrame.getFrames(), text="Tumor Detected",
height=1, width=20)

resLabel.configure(background="White", font=("Comic Sans MS", 16, "bold"),
fg="red")

else:

resLabel = tkinter.Label(self.FirstFrame.getFrames(), text="No Tumor", height=1,
width=20)

resLabel.configure(background="White", font=("Comic Sans MS", 16, "bold"),
fg="green")

resLabel.place(x=700, y=450)

elif (self.val.get() == 2):

self.listOfWinFrame = 0

self.listOfWinFrame = list()

self.listOfWinFrame.append(self.FirstFrame)
```

```
self.listOfWinFrame[0].setCallObject(self.DT)

self.listOfWinFrame[0].setMethod(self.DT.removeNoise)

secFrame = Frames(self, MainWindow, self.wWidth, self.wHeight,
self.DT.displayTumor, self.DT)

self.listOfWinFrame.append(secFrame)

for i in range(len(self.listOfWinFrame)):

if (i != 0):

self.listOfWinFrame[i].hide()

self.listOfWinFrame[0].unhide()

if (len(self.listOfWinFrame) > 1):

self.listOfWinFrame[0].btnView['state'] = 'active'

else:

print("Not Working")

mainObj = Gui()

from tensorflow.keras.models import load_model

import cv2 as cv

import imutils

model = load_model('brain_tumor_detector.h5')

def predictTumor(image):

gray = cv.cvtColor(image, cv.COLOR_BGR2GRAY)

gray = cv.GaussianBlur(gray, (5, 5), 0)

# Threshold the image, then perform a series of erosions +

# dilations to remove any small regions of noise

thresh = cv.threshold(gray, 45, 255, cv.THRESH_BINARY)[1]

thresh = cv.erode(thresh, None, iterations=2)

thresh = cv.dilate(thresh, None, iterations=2)

# Find contours in thresholded image, then grab the largest one
```

```
cnts = cv.findContours(thresh.copy(), cv.RETR_EXTERNAL,
cv.CHAIN_APPROX_SIMPLE)

cnts = imutils.grab_contours(cnts)

c = max(cnts, key=cv.contourArea)

# Find the extreme points

extLeft = tuple(c[c[:, :, 0].argmin()][0])

extRight = tuple(c[c[:, :, 0].argmax()][0])

extTop = tuple(c[c[:, :, 1].argmin()][0])

extBot = tuple(c[c[:, :, 1].argmax()][0])

# crop new image out of the original image using the four extreme points (left,
right, top, bottom)

new_image = image[extTop[1]:extBot[1], extLeft[0]:extRight[0]]

image = cv.resize(new_image, dsize=(240, 240), interpolation=cv.INTER_CUBIC)

image = image / 255.

image = image.reshape((1, 240, 240, 3))

res = model.predict(image)

return res

import tkinter

from PIL import ImageTk

from PIL import Image

class Frames:

xAxis = 0

yAxis = 0

MainWindow = 0

MainObj = 0

winFrame = object()

btnClose = object()

btnView = object()
```

```
image = object()

method = object()

callingObj = object()

labelImg = 0

def __init__(self, mainObj, MainWin, wWidth, wHeight, function, Object,
xAxis=10, yAxis=10):

self.xAxis = xAxis

self.yAxis = yAxis

self.MainWindow = MainWin

self.MainObj = mainObj

self.MainWindow.title("Brain Tumor Detection")

if (self.callingObj != 0):

self.callingObj = Object

if (function != 0):

self.method = function

global winFrame

self.winFrame = tkinter.Frame(self.MainWindow, width=wWidth,
height=wHeight)

self.winFrame['borderwidth'] = 5

self.winFrame['relief'] = 'ridge'

self.winFrame.place(x=xAxis, y=yAxis)

self.btnClose = tkinter.Button(self.winFrame, text="Close", width=8,

command=lambda: self.quitProgram(self.MainWindow))

self.btnClose.place(x=1020, y=600)

self.btnView = tkinter.Button(self.winFrame, text="View", width=8,
command=lambda: self.NextWindow(self.method))

self.btnView.place(x=900, y=600)

def setCallObject(self, obj):
```

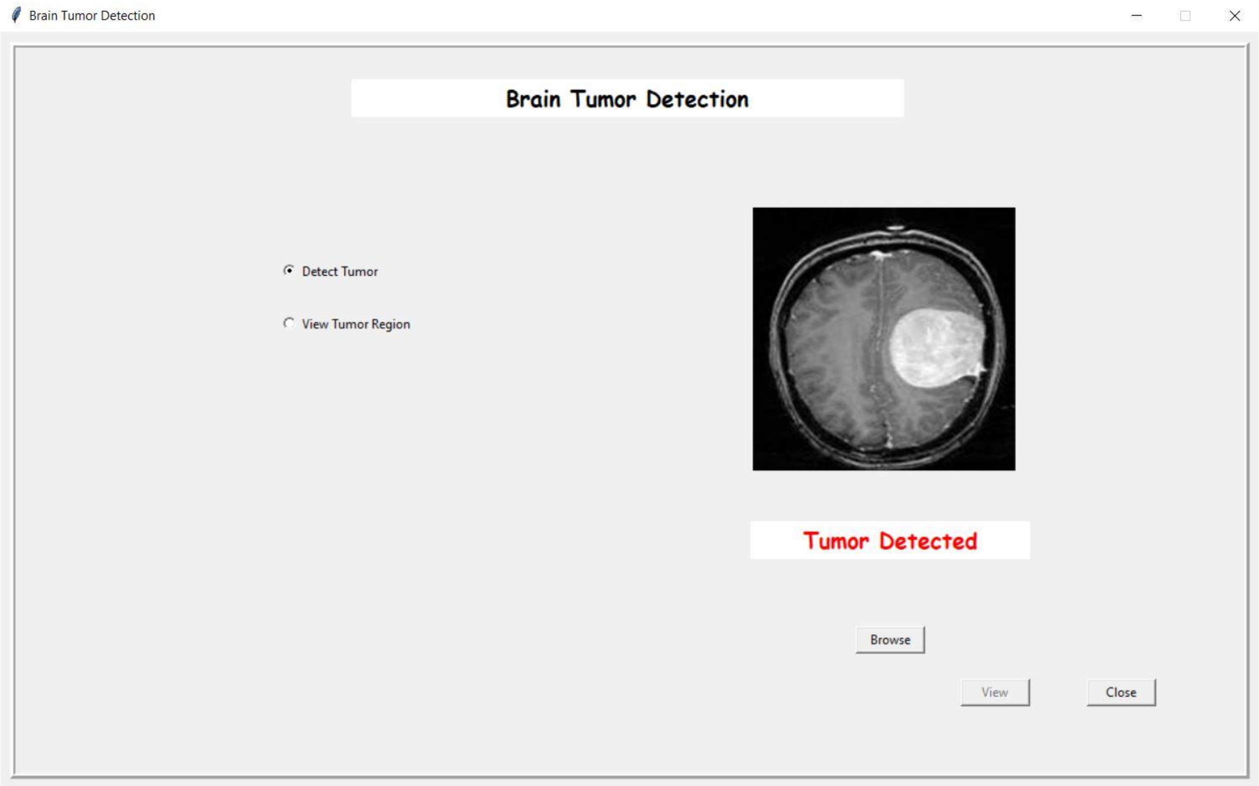
```
self.callingObj = obj
def setMethod(self, function):
self.method = function
def quitProgram(self, window):
global MainWindow
self.MainWindow.destroy()
def getFrames(self):
global winFrame
return self.winFrame
def unhide(self):
self.winFrame.place(x=self.xAxis, y=self.yAxis)
def hide(self):
self.winFrame.place_forget()
def NextWindow(self, methodToExecute):
listWF = list(self.MainObj.listOfWinFrame)
if (self.method == 0 or self.callingObj == 0):
print("Calling Method or the Object from which Method is called is 0")
return
if (self.method != 1):
methodToExecute()
if (self.callingObj == self.MainObj.DT):
img = self.MainObj.DT.getImage()
else:
print("Error: No specified object for getImage() function")
jpgImg = Image.fromarray(img)
current = 0
for i in range(len(listWF)):
```

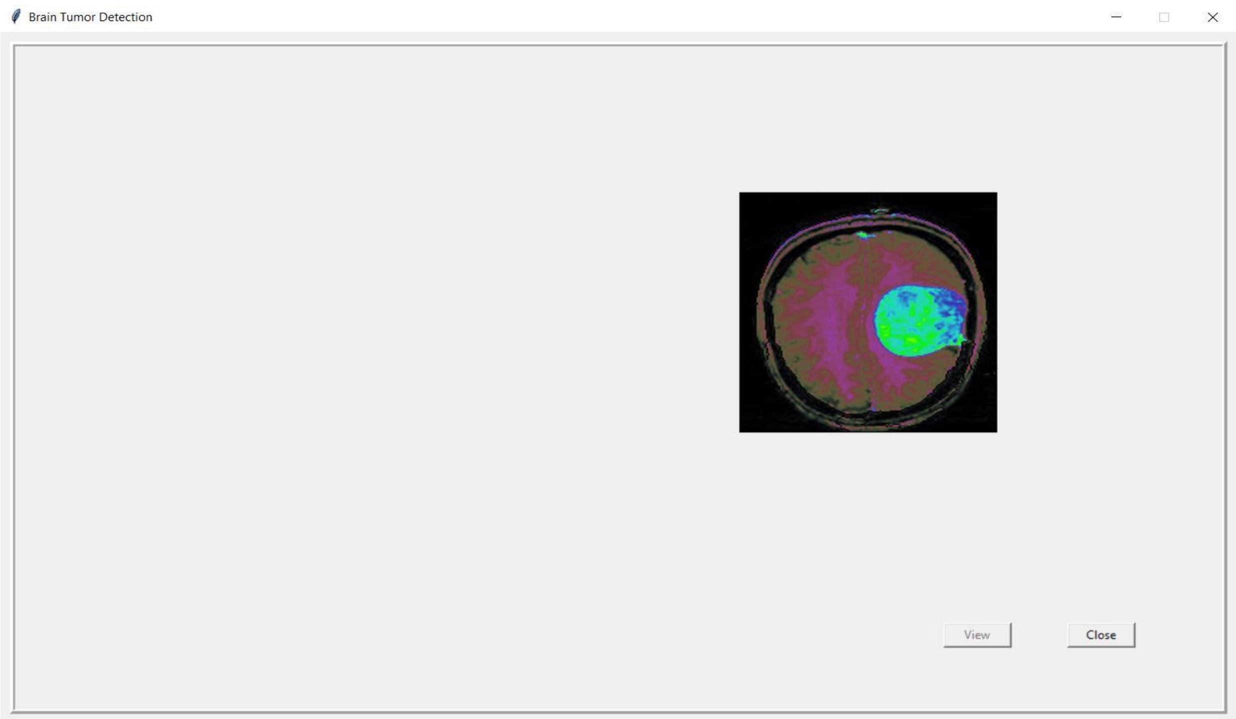
```
listWF[i].hide()
if (listWF[i] == self):
current = i
if (current == len(listWF) - 1):
listWF[current].unhide()
listWF[current].readImage(jpgImg)
listWF[current].displayImage()
self.btnView['state'] = 'disable'
else:
listWF[current + 1].unhide()
listWF[current + 1].readImage(jpgImg)
listWF[current + 1].displayImage()
print("Step " + str(current) + " Extraction complete!")
def removeComponent(self):
self.btnClose.destroy()
self.btnView.destroy()
def readImage(self, img):
self.image = img
def displayImage(self):
imgTk = self.image.resize((250, 250), Image.ANTIALIAS)
imgTk = ImageTk.PhotoImage(image=imgTk)
self.image = imgTk
self.labelImg = tkinter.Label(self.winFrame, image=self.image)
self.labelImg.place(x=700, y=150)

import numpy as np
import cv2 as cv
```

```
class DisplayTumor:
curImg = 0
Img = 0
def readImage(self, img):
self.Img = np.array(img)
self.curImg = np.array(img)
gray = cv.cvtColor(np.array(img), cv.COLOR_BGR2GRAY)
self.ret, self.thresh = cv.threshold(gray, 0, 255, cv.THRESH_BINARY_INV +
cv.THRESH_OTSU)
def getImage(self):
return self.curImg
# noise removal
def removeNoise(self):
self.kernel = np.ones((3, 3), np.uint8)
opening = cv.morphologyEx(self.thresh, cv.MORPH_OPEN, self.kernel,
iterations=2)
self.curImg = opening
def displayTumor(self):
# sure background area
sure_bg = cv.dilate(self.curImg, self.kernel, iterations=3)
# Finding sure foreground area
dist_transform = cv.distanceTransform(self.curImg, cv.DIST_L2, 5)
ret, sure_fg = cv.threshold(dist_transform, 0.7 * dist_transform.max(), 255, 0)
# Find unknown region
sure_fg = np.uint8(sure_fg)
unknown = cv.subtract(sure_bg, sure_fg)
# Marker labelling
ret, markers = cv.connectedComponents(sure_fg)
```

```
# Add one to all labels so that sure background is not 0, but 1
markers = markers + 1
# Now mark the region of unknown with zero
markers[unknown == 255] = 0
markers = cv.watershed(self.Img, markers)
self.Img[markers == -1] = [255, 0, 0]
tumorImage = cv.cvtColor(self.Img, cv.COLOR_HSV2BGR)
self.curImg = tumorImage.
from flask import Flask, render_template, request, jsonify
import os , shutil
from keras.models import load_model
import cv2 as cv
import imutils
@app.route('/detect')
def detect():
files = os.listdir(UPLOAD_FOLDER)
if len(files) == 0:
return 'No uploaded image found'
image_path = os.path.join(UPLOAD_FOLDER, files[0])
image = cv.imread(image_path)
if image is None:
return 'Error loading image'
result = predictTumor(image)
print(result)
```

SCREENSHOTS





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This is to certify that Mr / Ms **GOKUL K** has presented a paper titled **"Deep learning based 3D MRI image segmentation using CNN algorithm for detecting the brain tumor "** from **Prince Dr k Vasudevan college of engineering and technology** in the **"National Conference On Recent Trends In Analytics And Computing Technologies (RTACT 2024) held on 15th March 2024"** Organized by Department of AR and VR, Institute of CSE, SIMATS Engineering, SIMATS, Chennai - 602105.

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