# [P-1]

**A PRELIMENERY REPORT ON**

**BRAIN TUMOR DETECTION AND LEVEL PREDICTION SYSTEM**

SUBMITTED TO THE SAVITRIBAI PHULE PUNE UNIVERSITY, PUNE

IN THE PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE AWARD OF THE DEGREE

OF

**BACHELOR OF ENGINEERING (COMPUTER ENGINEERING)**

##### SUBMITTED BY

**ROHAN KHATODE B1909504264**

**ARANAV MAHALPURE B1909504273**

**ASHISH CHANDEKAR B1909504209**

**AAYUSH BHALAVI**  **B1909504217**



## DEPARTMENT OF COMPUTER ENGINEERING

**INTERNATIONAL INSTITUTE OF INFORMATION TECHNOLOGY, PUNE,**

**HINJEWADI, PUNE, MAHARASHTRA 411057**

## SAVITRIBAI PHULE PUNE UNIVERSITY

## 2024 -2025

**[P-2]**



**CERTIFICATE**

This is to certify that the project report entitles

**“BRAIN TUMOR DETECTION AND LEVEL PREDICTION SYSTEM”**

Submitted by

**ROHAN KHATODE B1909504264**

**ARANAV MAHALPURE B1909504273**

**ASHISH CHANDEKAR B1909504209**

**AAYUSH BHALAVI** **B1909504217**

is a bonafide student of this institute and the work has been carried out by him/her under the supervision of **Prof. Pallavi Yevale** and it is approved for the partial fulfillment of the requirement of Savitribai Phule Pune University, for the award of the degree of **Bachelor of Engineering** (Computer Engineering).

**(Prof. Pallavi Yevale)** **(Dr. Ajitkumar Shitole)**

Guide Head

Department of Computer Engineering Department of Computer Engineering

**(Dr. V. V. Patil)**

Principal,

International institute of information technology, Pune,

Place: Pune

Date:

**ACKNOWLEDGEMENT**

We would like to express our heartfelt gratitude to Prof. Pallavi Yevale, our internal guide, for her constant support and valuable guidance as we work on the ongoing project titled “**Brain Tumor Diagnosis and Grading Using Multi-Task Convolutional Networks on MRI Images**”. Her expertise and feedback have been instrumental in shaping the direction of this research, and we look forward to her continued mentorship as the project progresses.

We also extend our sincere thanks to Dr. Ajitkumar Shitole, Head of the Department, for providing us with the opportunity to undertake this project. The research involved has been a great learning experience, allowing us to explore advanced techniques in medical analysis, deep learning, and computer vision, particularly their application in brain tumor detection and segmentation systems.

We also extend sincere thanks to all the staff members of the Department of Computer Engineering and Dr. Vaishali V. Patil, Principal, for helping us in various aspects.

**NAME OF THE STUDENTS**

**ROHAN KHATODE (BEA56)**

**ARANAV MAHALPURE (BEA63)**

**ASHISH CHANDEKAR (BEA67)**

**AAYUSH BHALAVI (BEA09)**

**ABSTRACT**

Brain tumors are important medical issues and must be detected quickly and accurately to give the right treatment. Checking the MRI scans manually can be slow process and can have many human errors, so to make it easy and error-free, we use automated solutions, which are very important in the medical field. In our research, we found that there are many models that help us to find the brain tumors and the type of brain tumors. We reviewed the mostly used model known as Convolutional Neural Networks (CNN), which uses the BRATS dataset to create a better system for classifying and segmenting brain tumors. The aim is to improve both segmentation precision and classification accuracy, solving the problems while detecting the types and levels of brain tumor detection. The research used several deep learning methods. Techniques like Res-Net and VGG-Net, along with hybrid models such as Caps-Net and VGG-Net were applied. While these have helped find tumors better, gaps still exist in the research. A major issue is that there are not enough brain tumors classified thoroughly. Many models struggle to tell apart different tumors, and older methods often made mistakes in outlining the tumor areas on MRI scans. The approach of using deep learning boosts pixel-wise segmentation and enables accurate classification into different tumor types. It helps in clearly defining the tumor borders. This results in both tumor classification and segmentation, which can achieve high accuracy across various tumor types and levels.

**[P3]**

**TABLE OF CONTENTS**

LIST OF ABBREVATIONS i

LIST OF FIGURES ii

LIST OF TABLES iii

# CHAPTER TITLE PAGE NO.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Sr.No. | | | Title of Chapter | | Page No. |
| 01 | | | **Introduction** | | 1 |
|  | 1.1 | | Motivation | | 1 |
|  | 1.2 | | Problem Definition | | 2 |
| 02 | | | Literature Survey | | 3 |
| 03 | | | Software Requirements Specification | | 4 |
|  | | 3.1 | Introduction | | 4 |
|  | |  | 3.1.1 | Project Scope | 4 |
|  | |  | 3.1.2 | User Classes and Characteristics | 4 |
|  | |  | 3.1.3 | Assumptions and Dependencies | 6 |
|  | | 3.2 | Functional Requirements | | 6 |
|  | | 3.3 | External Interface Requirements (If Any) | | 7 |
|  | |  | 3.3.1 | User Interfaces | 7 |
|  | |  | 3.3.2 | Hardware Interfaces | 7 |
|  | |  | 3.3.3 | Software Interfaces | 8 |
|  | | 3.4 | Nonfunctional Requirements | | 8 |
|  | |  | 3.4.1 | Performance Requirements | 9 |
|  | |  | 3.4.2 | Safety Requirements | 9 |
|  | |  | 3.4.3 | Security Requirements | 9 |
|  | |  | 3.4.4 | Software Quality Attributes | 10 |
|  | | 3.5 | **System Requirements** | | 11 |
|  | |  | 3.3.1 | Database Requirements | 11 |
|  | |  | 3.3.2 | Software Requirements (Platform Choice) | 11 |
|  | |  | 5.3.3 | Hardware Requirements | 11 |
|  | | 3.6 | Analysis Models: SDLC Model to be applied | | 11 |
|  | | 3.7 | System Implementation Plan | | 12 |
| 04 | | | System Design | | 14 |
|  | | 4.1 | System Architecture | | 14 |
|  | | 4.2 | Data Flow Diagrams | | 15 |
|  | | 4.4 | UML Diagrams | | 16 |
| 05 | | | Other Specification | | 20 |
|  | | 5.1 | Advantages | | 20 |
|  | | 5.2 | Limitations | | 20 |
|  | | 5.3 | Applications | | 21 |
| 06 | | | **Conclusions & Future Work** | | 23 |
|  | | | **Appendix A**  **Appendix B**  **Appendix C** | | 24  26  27 |
|  | | | References | | 28 |

**LIST OF ABBREVATIONS**

|  |  |
| --- | --- |
| **Abbreviation** | **Illustration** |
|  |  |
| MRI | Magnetic Resonance Imaging |
| CNN | Convolutional Neural Networks |
| CT | Computed Tomography |
| AI  ML  BRATS | Artificial intelligence  Machine Learning  Brain Tumor Segmentation |

**LIST OF FIGURES**

|  |  |  |
| --- | --- | --- |
| **Figure** | **Illustration** | **Page No.** |
|  |  |  |
| 4.1  4.2.1 | System Architecture  DFD Level – 0 | 14  15 |
| 4.2.2 | DFD Level – 1 | 15 |
| 4.2.3 | DFD Level – 2 | 15 |
| 4.3.1 | Class Diagram | 16 |
| 4.3.2 | Use Case Diagram | 16 |
| 4.3.3 | Activity Diagram | 17 |
| 4.3.4 | Component Diagram | 18 |
| 4.3.5 | Sequential Diagram | 19 |
| 4.3.6 | Deployment Diagram | 19 |

**LIST OF TABLES**

|  |  |  |
| --- | --- | --- |
| **Table** | **Illustration** | **Page No.** |
| 1 | Literature Survey | 3 |

**CHAPTER 1**

**INTRODUCTION**

Brain tumors are a serious challenge in medical diagnosis because of the need for early detection to ensure the best possible treatment. MRI (Magnetic Resonance Imaging) is the method for detecting brain tumors, as it gives us clear images of the brain and the tumor present in the brain. When doing the analysis, these scans manually are taking more time and can give the errors.

The difficulties in this field come from the wide range of variation and similarities in brain tumor characteristics, like size and shape of the tumors, even within the same tumor type, which can lead to other diseases. Misdiagnosing a brain tumor can have the worst consequences for a patient’s chance of survival, which makes for an increased interest in automated image processing technologies as a solution to the limitations of manual diagnosis. We reviewed various algorithms for the detection and classification of brain tumors, with many studies focused on achieving high performance results and achieving low error rates. Deep learning algorithms, and specifically convolutional neural networks (CNN), are becoming more popular for the development of automated systems for accurate classification and segmentation of brain tumors, as in manual processes it is more time-consuming.

In many of the research papers, we found that many researchers have successfully used CNNs to classify brain tumors. Models like Res-Net, VGG-Net, and hybrid models such as Caps-Net, VGG-Net have shown improved accuracy in identifying tumors from MRI scans. These deep learning models are used for learning complex features on their own, providing better results than traditional methods, which were based on manually selecting features. Still, there are gaps, particularly in classifying specific types of tumors like gliomas, meningiomas, and pituitary tumor and the Levels in which The brain tumor lies. Many of the models only distinguish about the detection of brain tumors or give low precision, while segmentation (outlining the tumor's boundaries) is important.

**1.1 Motivation**

* **Importance of Diagnosis:**
  + Timely and accurate identification of brain tumors is critical for prognosis and treatment.
  + Brain tumors, both benign and malignant, pose severe health risks, including neurological damage and death.
* **Limitations of Traditional Methods:**
  + Diagnostic methods rely on radiologists manually examining MRI or CT scans.
  + The manual process is time-consuming and subject to variability due to human interpretation.
* **Growing Need for Automation:**
  + Increasing complexity of imaging data and demand for precise diagnoses highlight the need for automated systems.
  + Reliable and efficient systems are necessary to assist medical professionals in detecting and grading brain tumors.
* **Role of Deep Learning:**
  + Advancements in deep learning and AI provide a powerful solution for tumor detection and grading.
  + Machine learning models can automate the diagnostic process, reducing errors from fatigue or subjective judgment.

**1.2 Problem Definition**

This project aims to develop a system that automates the detection, classification, and severity prediction of brain tumors from MRI images. Traditional manual analysis of MRI scans is time-consuming and can lead to inconsistent results. By applying deep learning, the system will enable accurate tumor detection, identify tumor types, and predict severity levels, providing healthcare professionals with a reliable tool to improve diagnosis and treatment planning.

**CHAPTER 2**

**LITERATURE SURVEY**

1. **A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor**

Neelum Noreen et al proposed a multi-level feature extraction method based on the use of Inception-v3 and DenseNet201 models. Features in different layers were extracted and passed through a softmax classifier. The model was experimented on a publicly available dataset with three-class brain tumors. Inception-v3 achieved 99.34% and DenseNet201 99.51% accuracy. The result outperform all state-of-the-art deep learning techniques for the classification task.

1. **A Robust Approach for Brain Tumor Detection in Magnetic Resonance Images Using Finetuned EfficientNet**

Hasnain Ali Shah et al proposed Brain Tumor Detection Approach Using MRI Images by Using Effcetivnet B0. Improved images and data augmentation improved the quality and size of the dataset. The model had obtained high classi cation accuracy compared to VGG16 and InceptionV3. Automatic deep model is quite efficient for the diagnosis process. Improved accuracy in diagnosis was achieved comparing with conventional CNNs.

1. **A Two-Stage Generative Model with CycleGAN and Joint Diffusion for MRI-based Brain Tumor Detection**

Wenxin Wang et al demonstrated the techniques of VE-JP and CycleGAN for cancerous portion of brain tumour segmentation and detection. CycleGAN generates abnormal ones from normal images, where as VE-JP reconstructs normal images but takes into consideration only pathologic region. The hybrid has enabled precise segmentation for tumor. The focus was on joint probability for conditional generation. The model shows that great improvement has been made over existing methods.

1. **Abnormal Brain Tumors Classification Using ResNet50 and Its Comprehensive Evaluation**

Ayesha Younis et al was able to classify with better accuracy in using ResNet50 with transfer learning and data augmentation. The classification for brain tumor, such as meningioma, glioma, and pituitary gland tumors, is done. It can reach up to 99% accuracy for a dataset of 5712 images. The model uses regularization techniques to prevent overfitting. This model gave much better performance compared with other models.

1. **Automated Brain Tumor Segmentation and Classification in MRI Using YOLO-Based Deep Learning**

Maram Fahaad Almufareh et al has compared YOLOv5 and YOLOv7 about the detection of three types of brain tumors meningiomas, gliomas, and pituitary tumors detected from MRI images. The YOLO models were compared with the RCNN and Mask RCNN. According to the study, YOLO reported higher accuracy in detections. This study emphasized the progress in real-time tumor detection.

1. **Automated Segmentation of Brain Tumor MRI Images Using Deep Learning**

Surendran Rajendran et al exploited the U-Net architecture to attain brain tumor segmentation from MRI images. Here, an architecture was developed with skip connections as well as a fully convolutional design. It basically just extracted the fine details of the tumor from the MRI images. U-Net worked very well for precise detail-based segmentation. It is one of the most powerful architectures in the area of medical image applications.

1. **Brain Tumor and Glioma Grade Classification Using Gaussian Convolutional Neural Network**

Muhammad Rizwan et al implemented a classification of brain tumors using high-resolution MRI images by categorizing them as pituitary, glioma, and meningioma. Additionally, the sub-classification of gliomas into Grade-2, Grade-3, and Grade-4 also performed. This always used to grade the tumor and diagnosed it with more accuracy. GCNN would provide reliable performance for use in the clinical environment.

1. **Brain Tumor Classification and Detection Based DL Models: A Systematic Review**

Karrar Neamah et al reviewed deep learning models for the classification and detection of brain tumors from 2019 to 2022. The crucial models studied are CNNs, transfer learning, and hybrid techniques. Data augmentation, attention mechanisms, and diffusion models were discussed. After discussing various approaches, their strengths and limitations, the strengths and limitations together produced valuable insights for future research.

1. **Brain Tumor Detection and Multi-Grade Segmentation Through Hybrid Caps-VGGNet Model**

Ayesha Jabbar et al introduced a hybrid model called Caps-VGG-Net model for the detection and classification of tumours. It is a strong combination of CapsNet and VGGNet, which can be effectively trained on very large datasets. It was trained on high-quality images from BraTS-2020 and BraTS-2019 datasets. Amazing classification scores were achieved with this model. This approach helps in the automatic tumor classification by radiologists.

1. **Brain Tumor Identification and Classification of MRI Images Using Deep Learning Techniques**

Zheshu Jia et al presented a segmentation model based on structural, morphological, and relaxometry information. The algorithm was able to successfully overcome a few drawbacks that had been noted in the manual tumor detection process carried out by radiologists. FAHS-SVM integrated ELM training to maximize tumor and surrounding tissue segmentation accuracy. Uniformity was realized in tumor and surroundings segmentation. The model improved clinical practice settings with sensitivity and efficiency.

1. **Brain Tumor Segmentation Using S-Net and SA-Net**

Sunita Roy et al designed two new CNN models named S-Net and SA-Net for the brain tumor segmentation model. With a basic architecture of U-Net, Merge Blocks applied global and local context, while Attention Blocks did the trick in giving importance to areas of interest for better segmentation. Annotated samples were optimized along with data augmentation to ensure a proper use of models during training. It highlighted efficient performance in brain tumor segmentation using the above models.

1. **CorrDiff: Corrective Diffusion Model for Accurate MRI Brain Tumor Segmentation**

Wenqing Li et al proposed a correction diffusion model that corrects the systematic error in MRI segmentation. In this model, the Vector Quantized Variational Autoencoder is used for compressing and stabilizing data. Again, the Multi-Fusion Attention Mechanism is introduced to improve the performance of the model. The experiments are conducted on datasets including BraTS2019 and BraTS2020. It upgrades the accuracy of the model significantly in terms of segmentation.

1. **Enhancing Brain Tumor Diagnosis: Transitioning from Convolutional Neural Network to Involutional Neural Network**

Involutional Neural Networks (Inv-Nets) was proposed by et al Abdullah A. Asiri for brain tumor classification. Inv-Nets lowered the computational complexity compared to traditional CNNs. It was used for a four-class classification problem. The technique proved effective in resource-limited scenarios. This is one of the methods used for medical image analysis.

1. **Improved Classification of Different Brain Tumors in MRI Scans Using Patterned-GridMask**

Ji-Hyeon Lee et al used the Gaussian filters. To enhance generalizability, the technique applied GridMask. For partially occluded tumors, the proposed improvement is the use of a Patterned-GridMask. Four deep learning models: ViT-B/16, EfficientNetV2-M, were applied to the evaluation. The system has the potential for early detection and diagnosis of an advanced form.

1. **Improving Effectiveness of Different Deep Transfer Learning-Based Models for Detecting Brain Tumors from MR Images**

Sohaib Asif et al utilized AI and deep learning architectures for the early classification of brain tumors. Models utilized for the process are Xception, DenseNet121, and InceptionResNetV2 to extract features from MRI images. The models are tested on benchmark datasets performances using the ADAM optimization algorithm. Their model obtained high-performance accuracy in classification. Effective work for supporting automated medical imaging diagnosis.

1. **Improving Tumor Classification by Reusing Self-Predicted Segmentation of Medical Images as Guiding Knowledge**

Xiaoyi Lin et al improved the classification of brain tumour using EfficientNet-B0 on MRI images. Techniques in image enhancement and data augmentation are applied to enhance the approach. Deep learning models show improvement over traditional models VGG16 and InceptionV3 with high diagnostic accuracy as well as class-wise robust classification. This presents an interphase of fine-tuned architectures from deep learning.

1. **On the Performance of Deep Transfer Learning Networks for Brain Tumor Detection Using MR Images**

Saif Ahmad et al applied transfer learning techniques with 2D MR images for the purpose of classifying brain tumors. Models used included VGG-16, ResNet50, and DenseNet201. Transfer learning significantly improved the early diagnosis of brain tumors and helped in proper treatment. In the study, a labeled dataset comprising both normal and abnormal images of brain was used. The method enhanced the diagnosis accuracy compared to traditional methods.

1. **Optimized Brain Tumor Detection: A Dual-Module Approach for MRI Image Enhancement and Tumor Classification**

Abdullah A. Asiri et al The candidate used MRI diagnosis with diagnosis based on adaptive Wiener filtering and ICA. This removed noise and removed contrast variability in MRI images. SVM did a very good classification and segmentation of the tumors. The enhanced image gave automatic accuracy. The overall system improved the accuracy percentage in the diagnosis of brain-related cancerous diseases.

1. **ResUNet+: A New Convolutional and Attention Block-Based Approach for Brain Tumor Segmentation**

Sedat Metlek et al proposed a hybrid convolutional model for brain tumor segmentation. The model was strictly on a region of interest rather than processing the whole images. With reduced computational costs and better performance on segmentation, the approach was evaluated on datasets acquired from BraTS 2018, 2019, and 2020. The results obtained were highly efficient in the detection of tumors and their segmentation.

1. **RU-Net2+: A Deep Learning Algorithm for Accurate Brain Tumor Segmentation and Survival Rate Prediction**

Ruqsar Zaitoon et al has designed a model for the diagnosis of Brain Tumours using RU-Net2+ and DBT-CNN. The designed model performs tumor detection, segmentation, classification, and survival prediction. BraTS dataset is used for the training and test set of the proposed algorithm. The results proved to be very promising wherein it has rightly categorized the patients based on their survival rates with the DBT-CNN classifier. This has sorted the improvement in the care of a patient with the application of such an automatic system.

1. **Brain Tumor Detection and Classification Using Machine Learning: A Comprehensive Survey**

Javaria Amin et al presented a fractional-chicken swarm optimization approach for tumor classification. After proper optimization, the algorithm was applied to train a deep recurrent neural network (RNN). The proposed model classified the brain tumor with accurate severity level. Feature extraction along with noise reduction was included in some preprocessing techniques. The proposed system enhanced the precision in classification.

1. **Self-Supervised Tumor Segmentation with Sim2Real Adaptation**

Xiaoman Zhang et al proposed a self-supervised segmentation approach using a two-stage Sim2Real training regimen. For the pre-training phase, models were trained on simulated tumors and fine-tuned with real datasets such as BraTS2018 and LiTS2017. Features of interest were mapped directly to segmentation tasks by using the layer decomposition method, which had improved segmentation accuracy. Results were better compared to traditional methods.

1. **Severity Level Classification of Brain Tumor Based on MRI Images Using Fractional-Chicken Swarm Optimization Algorithm**

Dr. R. Cristin et al in his work utilized MRI-based brain tumor classification with the help of a fractional-chicken swarm optimization algorithm. The best result was achieved with the derivative factor combined with the behavior pattern of the chicken swarm and was trained as a deep RNN by optimizing the algorithm with excellent classification accuracy. The proposed approach efficiently classified the levels of severity of the tumor.

1. **VGG-SCNet: A VGG Net-Based Deep Learning Framework for Brain Tumor Detection on MRI Images**

Mohammad Shahjahan Majib et al proposed a computer-assisted approach for tumor segmentation and classification. The paper presents numerous experiments with hybrid models and 16 transfer learning models. The best performance was achieved by VGG-SCNet. The automatic system diagnosed more accurately than the manual ones. It is an early sensitive tumor detector with better clinical outcome.

1. **Znet: Deep Learning Approach for 2D MRI Brain Tumor Segmentation**

Mohammad Ashraf Ottom et al used encoder-decoder architectures with skip connections for 2D brain tumour segmentation task. Tehniques of data augmentation were utilised to reinforce the training. The proposed model showed impressive performance by achieving a high value of the dice similarity coefficient. The approach demonstrated good applicability for automatic tumour segmentation. Such a system has potential for clinical deployment.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Sr.NO** | **Paper Title** | **Publication** | **Dataset Characteristics** | **Model Architecture** |
| 1 | Znet: Deep Learning Approach for 2D MRI Brain Tumor Segmentation | IEEE | Publically Dataset of 20 images | Znet (U-Net or other CNN-based architectures tailored) |
| 2 | VGG-SCNet: A VGG Net-Based Deep Learning Framework for Brain Tumor Detection on MRI Images | IEEE | BRATS 2018 dataset | VGG-Net architecture |
| 3 | Severity Level Classification of Brain Tumor based on MRI Images using Fractional-Chicken Swarm Optimization Algorithm | IEEE | BRATS 2015 and BRATS 2018 | Fractional-CSO algorithm |
| 4 | Self-Supervised Tumor Segmentation With Sim2Real Adaptation | IEEE | BraTS2018 for brain tumor segmentation and LiTS2 | UNet as the backbone for the self-supervised learning method. |
| 5 | RU-Net2+: A Deep Learning Algorithm for Accurate Brain Tumor Segmentation and Survival Rate Prediction | IEEE | (BraTS) dataset | RU-Net2+ for tumor segmentation and the DBT-CNN for classification |
| 6 | Brain tumor detection and classification using machine learning | IEEE | BRATS series | ResNet and DenseNet. |
| 7 | ResUNet+: A New Convolutional and Attention Block-Based Approach for Brain Tumor Segmentation | IEEE | BraTS (Brain Tumor Segmentation) datasets from 2018, 201, and 2020. | ResUNet+ architecture |
| 8 | Optimized Brain Tumor Detection: A Dual-Module Approach for MRI Image Enhancement and Tumor Classification | IEEE | (CE-MRI) images. | (SVM) & adaptive Wiener filtering, neural networks |
| 9 | On the Performance of Deep Transfer Learning Networks for Brain Tumor Detection Using MR Images | IEEE | MRI dataset sourced from Kaggle | (CNN) architectures |
| 10 | Improving Tumor Classification by Reusing Self-Predicted Segmentation of Medical Images as Guiding Knowledge | IEEE | pNENs-Grade Dataset HCC-MVI Dataset: ISIC 2017 Dataset | RS2-net architecture |
| 11 | Improving Effectiveness of Different Deep Transfer Learning-Based Models for Detecting Brain Tumors From MR Images | IEEE | Two publicly available datasets | Xception NasNet Large DenseNet121 InceptionResNetV2 |
| 12 | A Robust Approach for Brain Tumor Detection in Magnetic Resonance Images Using Finetuned EfficientNet | IEEE | The dataset contained 3762 MR images, 3060 were used as a subset, and 1500 were labelled as 1 (tumors). The other 1500 scans were labelled as 0 (non-tumor). | CNN , EfficientNet-B0 model |
| 13 | Automated Brain Tumor Segmentation and Classification in MRI Using YOLO-Based Deep Learning | IEEE | The Brain Tumor dataset of Southern Medical University. All the images in the dataset belong to any of the three tumor classes: meningioma, glioma, and pituitary | YOLO V5 MODEL,YOLO V7 MODEL |
| 14 | Brain Tumor and Glioma Grade Classification Using Gaussian Convolutional Neural Network | IEEE | T1-weighted complexity improved pictures. Three kinds of BTs (i.e., pituitary, glioma, and meningioma) are procured from 232 patients. | GCNN model |
| 15 | Brain Tumor Detection and Multi-Grade Segmentation Through Hybrid Caps-VGGNet Model | IEEE | In this research, the BraTs 2020 dataset was utilized. | VGGNet and CapsNet models |
| 16 | Brain Tumor Classification and Detection Based DL Models: A Systematic Review | IEEE | These datasets include a wide variety of MR images collected from patients with various forms of brain tumors, including tumor grades, sizes, and locations. | convolutional neural networks (CNNs) and recurrent neural networks (RNNs) |
| 17 | Brain Tumor Identification and Classification of MRI images using deeplearning techniques | IEEE | MRI images Dataset | A Fully Automatic Heterogeneous Segmentation using Support Vector Machine (FAHS-SVM) |
| 18 | Abnormal Brain Tumors Classification Using ResNet50 and Its Comprehensive Evaluation | IEEE | The dataset used in this study consisted of a total of 7,023 images which were categorized into four distinct classes: glioma,meningioma, no tumor, and pituitary. | Convolutional Neural Networks (CNN) |
| 19 | A Two-Stage Generative Model with CycleGAN and Joint Diffusion for MRI-based Brain Tumor Detection | IEEE | BraTs2020 .The dataset is consisted of glioma images provided by Multimodal Brain Tumor Segmentation Challenge (BraTs2020). | Variance Exploding (VE) SDE in the score-based generative models (SGMs) |
| 20 | Automated Segmentation of Brain Tumor MRI Images Using Deep Learning | IEEE | MRI images Dataset | Convolutional Neural Networks (CNN) |
| 21 | Brain Tumour Segmentation Using S-Net and SA-Net | IEEE | BraTS 2018, BraTS 2019, BraTS 2020, and BraTS 2021 | U-Net Model |
| 22 | CorrDiff: Corrective Diffusion Model for Accurate MRI Brain Tumor Segmentation | IEEE | BRATS2020 and BRATS2019 | First Stage: U-Net Segmentation , Second Stage: Corrective Diffusion Model, Vector Quantized Variational Autoencoder,Multi-Fusion Attention Mechanism. |
| 23 | CrossTransUnet: A New Computationally Inexpensive Tumor Segmentation Model for Brain MRI | IEEE | BraTS2020 challenge database | U-Net Model |
| 24 | Enhancing Brain Tumor Diagnosis: Transitioning From Convolutional Neural Network to Involutional Neural Network | IEEE | There are a total of 7023 human brain images. These images are classified into four classes: glioma (1321 images), no tumor (1595 images), pituitary(1457 images), and meningioma (1339 images). | Convolutional Neural Networks (CNN) |
| 25 | A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor | IEEE | 3064 T1-weighted contrast MR images of 233 Three different types of tumors such as meningioma, glioma, and pituitary are existing in this dataset. | PRE-TRAINED INCEPTION-V3 ,PRE-TRAINED DENSNET201 |

**CHAPTER 3**

**SOFTWARE REQUIREMENT SPECIFICATION**

**3.1 Introduction**

The purpose of this Software Requirement Specification (SRS) document is to define the software requirements for the Brain Tumor Detection and Level Prediction System. This system aims to automate the detection of brain tumors and predict their severity levels based on MRI scans using machine learning techniques.

**3.1.1 Project Scope: Brain Tumor Detection and Level Prediction System**

**1. Project Overview**

This project proposes to develop an automated system for detecting brain tumors and predicting levels of severity based on applications of deep learning techniques. The desire is that a model should be developed which will properly present the identification of tumors in MRI scans with the possibility of their further classification into subsequent levels of severity, such as low-grade or high-grade tumors. This shall do image processing and run machine learning algorithms where it will use to assist doctors for some quicker and more accurate diagnoses in order to drive better patient outcomes.

**2. Key Features**

* **Automated Tumor Detection:** The system will process brain MRI scans and identify the presence of tumors, providing a diagnosis based on predefined categories (e.g., tumor or no tumor).
* **Severity Level Prediction:** After detecting a tumor, the system will classify the severity or stage of the tumor.
* **User-Friendly Interface:** A simple graphical user interface (GUI) built with Tkinter will allow non-technical users, such as healthcare professionals, to upload MRI scans and view results.
* **Model Performance Metrics:** The system will provide insights into model performance, including metrics such as accuracy, precision, recall, and F1 score, helping stakeholders evaluate its effectiveness.

**3.1.2 User Classes and Characteristics**

1. **Healthcare Professionals (Radiologists, Neurologists)**

* Characteristics: These users are medical professionals responsible for diagnosing and treating brain tumors. They have an understanding of medical imaging and tumor classification.
* Needs: They need an accurate and efficient tool to help detect tumors and predict their severity, reducing the time required for manual diagnosis and increasing the accuracy of treatment planning.
* Interaction with the System: Healthcare professionals will upload MRI scans, review the automated analysis, and make clinical decisions based on the system’s findings.

1. **Data Scientists/Machine Learning Engineers**

* Characteristics: These users have technical expertise in data science, machine learning, and image processing. They are familiar with deep learning frameworks (e.g., TensorFlow, Keras) and medical imaging techniques.
* Needs: They need the ability to train, test, and fine-tune the tumor detection and prediction models. They may also require access to data, model metrics, and performance reports.
* Interaction with the System: Data scientists interact with the system during model development and refinement, focusing on improving classification accuracy and ensuring the model generalizes well to different datasets.

1. **Patients and Family Members**

* Characteristics: These users are patients undergoing diagnosis or treatment for brain tumors, or their family members. They may have limited knowledge of medical imaging and diagnostic tools.
* Needs: Patients and families need clear and understandable information about the diagnosis and severity of brain tumors to make informed decisions about treatment.
* Interaction with the System: They will receive reports or results generated by the system from healthcare professionals but do not directly interact with the classification model.

1. **Hospital IT Administrators**

* Characteristics: These users manage the integration and operation of the system within the hospital's IT infrastructure. They are responsible for ensuring the system functions smoothly and complies with regulatory standards.
* Needs: IT administrators require a well-documented API or interface to integrate the system with existing hospital software. They also need access to system logs and monitoring tools to ensure the system operates reliably.
* Interaction with the System: They handle the backend of the system, ensuring that it integrates with existing medical imaging tools and is compliant with data security and patient privacy regulations.

1. **Researchers/Academics**

* Characteristics: These users are engaged in medical research, studying brain tumor detection methods, or AI-based diagnostics. They may be involved in medical or AI research fields such as radiology, computer science, or biomedical engineering.
* Needs: Researchers need access to data insights, model performance reports, and technical details about the algorithms used. They are also interested in the broader implications of AI in medical diagnostics.
* Interaction with the System: Researchers will analyze the effectiveness of the system and contribute to its improvement by suggesting model enhancements or exploring new applications for AI in healthcare.
  + 1. **Assumptions and Dependencies**

**Assumptions:**

1. **High-Quality MRI Data:** It is assumed that the training and testing MRI datasets are of high quality, accurately labeled, and representative of real-world cases.
2. **Feature Representations:** The assumption is that image features (e.g., texture, shape, and intensity) effectively capture tumor characteristics and help in accurate detection.
3. **Model Training Success**: It is assumed that the selected deep learning model architecture will successfully classify brain tumors and predict their severity levels.
4. **Scalability of the System**: The system is expected to handle increasing numbers of patients and larger datasets without significant performance degradation.

**Dependencies:**

1. **Data Availability:** The project is dependent on the availability of MRI datasets labeled with tumor presence and severity information.
2. **Model Development:** The success of the project depends on selecting and optimizing the appropriate deep learning model architecture for medical image analysis.
3. **Hardware Resources:** The project requires access to sufficient computational resources, such as GPUs, to handle large image datasets and complex model training.
4. **Stakeholder Collaboration:** The project relies on active collaboration with medical professionals, hospitals, and research institutions for data collection, testing, and validation.

**3.2 Functional Requirements**

The system must be capable of analyzing MRI scans to detect and classify brain tumors into predefined categories, such as Glioma, miningioma, pituitary or no tumor.

1. **Data Collection**

* **MRI Data Access**: The system shall access MRI datasets containing labeled brain tumor images from reliable medical imaging sources.

1. **Data Preprocessing**

* **Image Standardization**: The system shall standardize MRI images by resizing and normalizing them to ensure consistency in input format.
* **Data Augmentation**: The system shall apply augmentation techniques (e.g., rotation, flipping) to increase dataset diversity and improve model robustness.

1. **Tumor Detection and Segmentation**

* **Image Segmentation Model**: The system shall employ a U-Net model for segmenting tumor regions in 2D MRI slices.
* **Tumor Boundary Detection**: The system shall highlight and delineate the boundaries of identified tumor regions on each MRI slice.

1. **Tumor Classification and Level Prediction**

* **Classification Model Training**: The system shall support the training of classification models (e.g., ResNet) on labeled MRI data to categorize tumor types.
* **Level Prediction**: The system shall predict the tumor’s severity level, providing insights into its aggressiveness.

1. **User Interface**

* **Input Functionality**: The system shall provide a user-friendly interface for users to upload MRI images for analysis.
* **Output Display**: The system shall display segmented images with highlighted tumor regions, classification results, and severity predictions in a clear and accessible format.

**3.3 External Requirements**

**3.3.1 User Interface**

1. The user interface of the Brain Tumor Detection System is meticulously designed for effortless interaction, ensuring a seamless experience for both users and medical professionals.
2. For radiologists, the interface features an intuitive dashboard displaying real-time scan data and comprehensive analytics. A user-friendly classification panel allows radiologists to swiftly verify whether scans show tumors.
3. Users have access to an easy-to-navigate panel where they can filter and view classified scans based on their preferences.
4. Users can provide feedback on scan classifications to flag cases that require additional review.

**3.3.2 Hardware Interface**

The hardware interface requirements for the brain tumor detection system using deep learning are critical for efficient model development and training. These requirements are primarily centered around the hardware components needed to execute deep learning tasks effectively.

The system integrates with various external hardware, high-speed internet connections, distributed computing, external devices, and cooling systems, as the system consumes significant power.

1. **Internet Connection**: A stable and high-speed internet connection is essential for downloading datasets, libraries, and pre-trained models, as well as collaborating with cloud-based services and remote teams.
2. **Distributed Computing:** If working with large datasets or training complex models, hardware interfaces for distributed computing (e.g., a cluster of GPUs) may be required.
3. **External Displays:** Having one or more external displays can facilitate monitoring training progress, debugging, and visualization.

**3.3.3 Software Interface**

1. **Database Integration:**

Integrate with databases to securely store and retrieve patient data, MRI scans, and analysis reports.

1. **User Feedback Portal:**

Develop a feedback portal where radiologists and other users can report misclassifications, request additional reviews, and provide system feedback.

1. **Authentication and Authorization:**

Implement secure authentication and authorization mechanisms to control access, ensuring only authorized healthcare professional access sensitive data.

1. **Monitoring and Logging Tools:**

Integrate monitoring tools to track system performance, maintain logs for audit trails, and generate performance and usage reports to support reliability and transparency.

**3.4 Non-Functional Requirements**

**3.4.1 Performance Requirements**

1. **Response Time:**

The system shall provide brain tumor detection and classification results within 5 seconds of receiving an MRI scan input.

1. **Throughput:**

The system shall support at least 50 concurrent users uploading MRI scans and receiving predictions simultaneously without degradation in performance.

1. **Scalability:**

The system shall be designed to scale horizontally to accommodate an increasing number of users, MRI scans, and data volume without requiring significant re-architecture.

1. **Model Training and Update Frequency:**

The deep learning model shall be retrained with updated MRI data and annotations at least once a month to maintain accuracy and relevance. The retraining process shall complete within 1 hour to minimize downtime for prediction services.

1. **Availability:**

The system shall maintain an uptime of 99.5%, ensuring reliability and availability for users to access predictions and diagnostic data.

**3.4.2 Safety Requirement**

* 1. **Error Handling**: The system must include mechanisms to handle unexpected inputs (e.g., corrupted MRI images) gracefully without crashing, notifying users or administrators if a scan could not be processed.
  2. **Model Interpretability**: To ensure safe use of the model, it should include features that help users understand why a scan was classified as indicative of a tumor, such as highlighting key regions that triggered the classification.
  3. **Failure Recovery**: The system should be designed to recover quickly from failures, with minimal data loss. It should save progress periodically during batch processing to avoid reprocessing large datasets in case of failure.

**3.4.3 Security Requirements**

1. **Data Privacy:** The system must comply with data protection regulations ensuring that patient data, including MRI content and identifiers, is handled securely.
2. **Access Control**: Only authorized users (e.g., medical professionals and administrators) should be able to access sensitive features such as training data and model predictions.
3. **Encryption**: Data transmission between the user interface and backend, as well as between system components, should be encrypted to prevent unauthorized access.
4. **Secure Model Storage**: The trained models and databases should be stored securely, with access restricted to authorized personnel to prevent unauthorized modifications.

**3.4.4 Software Quality Attributes**

1. **Reliability:** Under the same circumstances of scanning the brain, the system has to provide consistent output. The correctness percentage in classifying images should not vary much over time due to a change in data processing or hardware.
2. **Maintainability:** The code base should be modular and well-documented so that developers can update or alter pieces of code freely, like model architecture or the user interface, without affecting other parts of the system.
3. **Usability:** The GUI should be intuitive, that is, have a simplified structure to enable nontechnical users, such as clinicians, to input imaging data quickly and easily and display results. In the case of input anomalies or processing errors, clear error messages should be generated.
4. **Adjustability:** The system should allow for adjustability for use across other imaging platforms and contexts so that when faced with various kinds of brain tumors or evolving imaging techniques, the model may be successfully retrained on new datasets to be effective with time as medical practices change along with the change in the technology of imaging.
5. **Portability:** A system designed to support all operating systems will be deployment-environment-independent, thus flexible. Use of Python as the primary language and combining it with cross-platform libraries supports this requirement.
6. **Efficiency:** The system should employ the minimum possible processing time and memory by ensuring that the significant volumetric data in imaging will be provided without requiring a lot of hardware. Model compression and data caching are efficiency techniques.

**3.5 System Requirements**

**3.5.1 Database Requirements**

The database requirements for the brain tumor detection and level prediction system are:

* The database should be able to store and retrieve imaging data, such as MRI or CT scans, patient labels, and predictions, in a structured and efficient way.
* The database should support operations for processing imaging data, such as segmentation and feature extraction, either natively or through integration with external frameworks, such as TensorFlow or PyTorch.
* The database should ensure the security and privacy of the imaging data, especially if it contains sensitive patient information, by implementing encryption, authentication, or access control mechanisms.

**3.5.2 Hardware Requirements**

* CPU: Intel Core i5 or equivalent
* RAM: 16GB or more
* Storage: 128GB or more
* Internet: A high-speed connection

**3.5.3 Software Requirements**

* O/S: Preferred Windows
* Technology/Language: Python
* Database: MySQL

The database should provide a user-friendly and interactive interface for the project stakeholders, such as developers, analysts, or medical professionals, to query, visualize, or manipulate the imaging data, either through a web application or a command-line tool.

**3.6 Analysis Model: SDLC**

1. **Planning Phase:**

* Project Initiation: In this phase, the project is conceived, and initial planning activities occur. The project's objectives, scope, assumptions, dependencies, and non-functional requirements are defined. Stakeholders are identified, and the project team is formed.
* Analysis: During the analysis phase, the team identifies the specific requirements for data collection, model development, and system integration. Data sources are evaluated, and a strategy for obtaining labeled data (e.g., annotated medical imaging) is determined. The project's ethical and legal implications are also analyzed at this stage.

1. **Design Phase:**

* System Design: The system's architecture and components are designed, including the choice of deep learning model architecture, feature extraction techniques, and the real-time processing pipeline. The design should consider scalability, security, and ethical considerations.

1. **Implementation Phase:**

* Model Development: The deep learning model is developed, and the training process is carried out using the collected data. Model training, hyperparameter tuning, and evaluation are crucial activities in this phase.
* Real-Time Processing: The system's real-time imaging analysis functionality is implemented, integrating the trained model for live predictions.

1. **Testing Phase:**

* Unit Testing: Individual components, such as data preprocessing and feature extraction, are tested to ensure their correctness.
* Integration Testing: The various system components are integrated and tested to ensure that they work together as intended.
* User Feedback Mechanism Testing: The user feedback mechanism is tested to ensure that users can effectively report false positives and negatives.

1. **Deployment Phase:**

* The system is deployed in the target clinical environments, integrated through APIs or web widgets. Medical professionals start interacting with the system, and user engagement with the diagnostic system is monitored.

1. **Operation and Maintenance Phase:**

* Ongoing monitoring and maintenance are essential to ensure the system's reliability, accuracy, and adherence to ethical and legal standards. A crisis management plan is developed to address unexpected issues related to diagnostic predictions. User feedback is continuously collected and used to improve the system's accuracy and performance.

1. **Monitoring and Evaluation:**

* The system is continually monitored for its performance, scalability, and compliance with non-functional requirements. User feedback and system logs are analyzed to refine the model and improve prediction accuracy.

1. **Feedback Loop:**

* The SDLC process is iterative, with feedback loops that lead to refinements and enhancements to the system based on user feedback, changing clinical practices, and evolving medical imaging technologies. Throughout the SDLC, ethical considerations, legal compliance, and scalability are woven into the development process. Regular assessments of the system's transparency, explainability, and user experience are performed to ensure the project's success and continued effectiveness in addressing the problem of brain tumor detection and level prediction. The SDLC provides a structured approach to manage the project from initiation to ongoing operation and improvement.
  1. **System Implementation Plan**

**Phase 1**: Problem Definition and Literature Review (1-2 weeks):

* Identify key goals, like classifying and segmenting brain tumors in MRI scans.
* Review recent research on segmentation and classification techniques (e.g., U-Net, CNNs) and common metrics (e.g., Dice score, accuracy).

**Phase 2**: Data Collection and Exploration (1-2 weeks):

* Collect MRI scans and segmentation labels (e.g., BraTS dataset with T1, T1CE, T2, FLAIR).
* Explore data distribution and any preprocessing requirements.

**Phase 3**: Data Preprocessing (2-3 weeks):

* Standardize images (normalize, resize) and apply augmentations (rotation, flipping) for model robustness.
* Split the dataset into training, validation, and test sets, ensuring no patient data leakage.

**Phase 4**: Model Development (3-4 weeks):

* Implement and train a U-Net (or variant) for segmentation, identifying tumor regions.
* Develop a CNN-based model for classifying tumor types or combine both in a multi-task learning model.

**Phase 5**: Model Evaluation (2-3 weeks):

* Measure segmentation performance (e.g., Dice coefficient, Jaccard index) and classification metrics (accuracy, F1 score).
* Compare against baseline models and literature to assess the results.

**Phase 6**: Model Optimization (1-2 weeks):

* Optimize hyperparameters (learning rate, batch size) and apply advanced techniques like attention mechanisms for improved accuracy.
* Perform model fine-tuning based on validation performance.

**Phase 7**: Integration and System Testing (2 weeks):

* Build an integrated system that outputs segmented regions and classification predictions for input MRI scans.
* Test the pipeline end-to-end on unseen data to ensure reliability.

**Phase 8**: Finalization and Documentation (1 week):

* Compile results and write the final report and documentation.

**CHAPTER 4**

**SYSTEM DESIGN**

* 1. **SYSTEM ARCHITECTURE**

**Training Phase**

Preprocessing

Train

Images

Giloma

Classification

Freatures

Extrasction

Meningioma

Database

Pituitary

**Testing Phase**

Preprocessing

No

Tumor

Identification

Freature Extraction

Test

Images

Fig 4.1 Architecture Diagram

**4.2 DATA FLOW DIAGRAMS**

Collect the Data ,verifies Dataset & processing the Procedure

Classifcation with ML and redirect to Result

User

Admin

Dataset collected & start Process

Collect the Data ,verifies Dataset & processing the Procedure

User

Segmentation Processing

Performance analysis used to predict the Result

Admin

Input the data & Collect the Dataset

Segmentation Process

Dataset are collection and

Preprocessing

User

Using Analysis output is generated and used to Predict the result

Feature extraction & classification using CNN

Admin

Fig 4.2 Data flow Diagram

**4.3 UML DIAGRAMS**

4.3.1 Class Diagram:

Resize image: Image

Normal:image

Resuze:Image

Normalize():Array

User Input

Imagepath: string

Imagedata: Image

Upload Image: Image

ValidateInput: Boolean

Image Processor

Feature extractor

Feature: Array

Extract: array

Detectedges: Image

segmentationmodel

DL Segmentation

User Input

modelPath : String

Segmentedimage: Image

LoadModel(); String

Segment() : Image

trainModel(Dataset) : Image

Predict(): Image

Imagepath: string

Imagedata: Image

Upload Image: Image

ValidateInput: Boolean

Report

tumor

tumorLevel : string  
settumor (): void

Setstage (): Void

Gettumor () : String

PatientID : String

Date: date

GenerateReport () : String

4.3.2 Use Case Diagram:

MRI Image Upload

Preprocessing

User ID

<<include>>s

<<include>>s

Tumor Segmentation

Tumor Detection

<<extends>>

<<extends>>

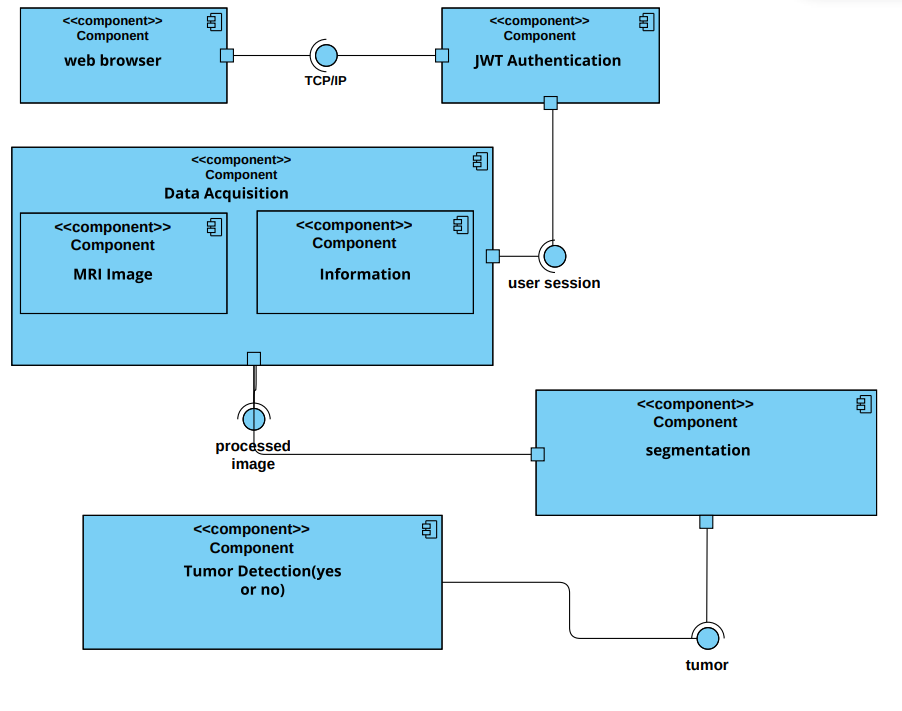
Visualize Result

Tumor Classification

Generate report

Classification of Result

* + 1. Component Diagram:

****

4.3.5 Sequential Diagram:

User

Server

Input Image

Image Preprocessing

Image Segmentation

Two Path Way Convolutional network

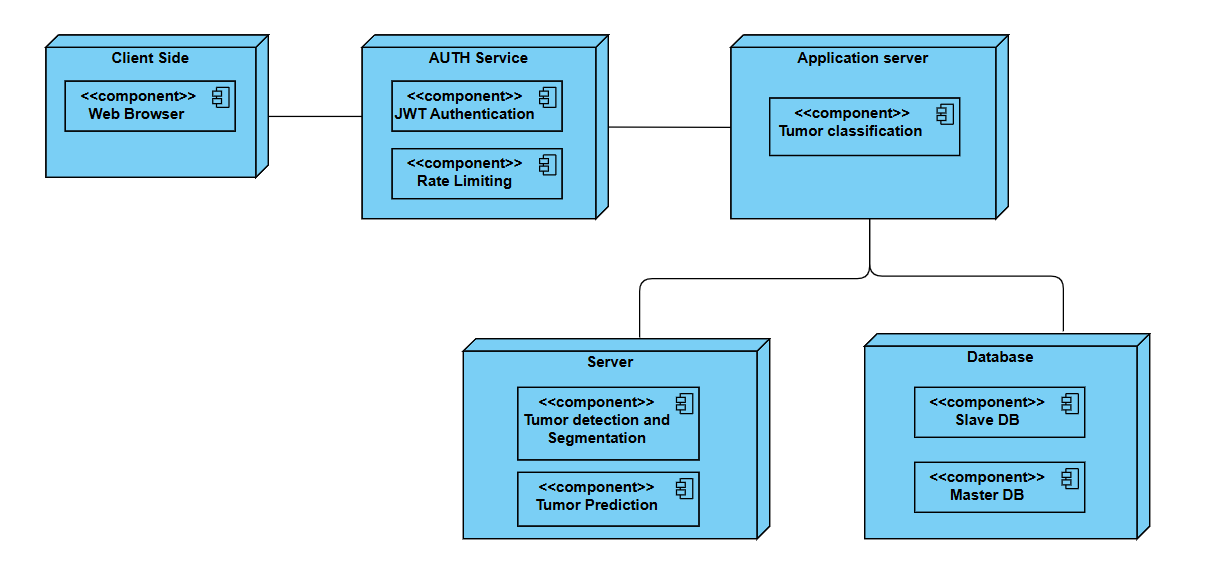
Feature Selection

Tumor detection and Grading

Display Result

s

4.3.6 Deployment Diagram:



**CHAPTER 5**

**OTHER SPECIFICATION**

**5.1 Advantages**

* **Improved Patient Safety:** The system enables the early detection of brain tumors, thus probably saving lives as a result of providing timely warnings and predictions in conduction with imaging data. This leads to better clinician response and patient care.
* **Scalability for Healthcare Platforms:** It is possible to offer true online and batch processing with the model. Therefore, it can be used in a variety of environments, from small clinics to hospitals possessing huge databases of patients. It can increase or decrease in size without affecting its performance.
* **Reduces Radiologist Workload:** The system, by automating the identification and classification of brain tumors, will significantly relieve workload for the radiologists. In doing so, they would have adequate time to pay more attention to intricate cases that are judgments or require trenchant analysis, thus increasing job satisfaction and minimizing burnouts.
* **Ease of User Interface:** The GUI is interactive for even the non-technical users like the medical staffs to be able to access, understand results, or interact with the detection system without knowledge of programming; thus, intuitive design helps in training and minimizes the learning curve.
* **Real-Time Feedback and Alerts:** The system may give real-time feedback to clinicians where any abnormal findings will be detected allowing immediate actions and improvement of patients.

**5.2 Limitations**

* **Contextual Challenges**: The system may struggle to accurately interpret the nuances of imaging data, potentially leading to misclassifications, such as false positives (healthy scans flagged as tumors) or false negatives (tumors missed). This highlights the need for continued clinician involvement in the diagnostic process.
* **Bias in Training Data**: The quality and balance of the training data directly influence the model’s performance. If the data contains inherent biases, the model may exhibit skewed results, potentially affecting specific patient demographics and leading to health disparities.
* **Evolving Medical Standards**: Advances in medical imaging and evolving clinical practices may render a model trained on outdated data less effective over time. Regular updates and retraining are necessary to maintain accuracy, which requires ongoing collaboration with medical experts.
* **Interpretability**: Deep learning models can be complex and opaque, making it challenging to understand the rationale behind a particular classification. This can complicate discussions with patients or medical staff regarding diagnostic decisions, necessitating the development of interpretability tools to explain model outputs.
* **Dependence on Quality Data**: The system’s performance is highly dependent on the quality and diversity of the training data. Insufficient or low-quality data can adversely affect the accuracy and reliability of the predictions.

**5.3 Applications**

* **Healthcare Institutions:** It can be incorporated into hospitals and clinics to facilitate the monitoring and diagnosis by radiologists of brain tumors resulting from imaging studies, hence ensuring timely interventions. This boosts cooperation in multidisciplinary teams.
* **Telemedicine Platforms:** It can advance remote diagnosis since it provides healthcare professionals equipment for analyzing imaging data as well as forecasts hence increasingly facilitating patient access to specialized care especially in rural areas or underserved settings.
* **Research Institutions:** The system can be applied in research to carry out the analysis of big databases containing brain scans in order to detect patterns and trends of appearance and development for tumors. This will give researchers a breakthrough in understanding the biology of tumor and responses for therapy.
* **Medical Training and Education:** The system can be used by the medical schools and training programs to provide students with the practical experience of analyzing imaging data and being aware of the classifications of tumor. This will help the future doctors while they practice.
* **Medical Online Publications:** Deployed in the comment sections of medical articles, the system will ensure that any discussion remains constructive and respectful so that the core topics of clinical stay as the focal point of the discussion, thus limiting the spread of misinformation and bringing evidence-based discussions to the forefront.
* **Clinical Trials:** In clinical trials, the model can be used in monitoring the patient's response to treatments on analyzing imaging data over time, thus providing insight into tumor progression and efficacy of treatments.

hg

* **Healthcare Analytics:** The system can support broader healthcare analytics through the compilation of detection information and classification about brain tumors and assist public health officials in comprehending how resources and efforts are exerted over time.

**CHAPTER 6**

**CONCLUSION AND FUTURE WORK**

We concluded that the most efficient approach for our project is to use a (CNN) after reading numerous research papers on the segmentation and classification of brain tumors. CNNs are more efficient at recognizing pictures and medical image analysis, which makes them more appropriate for brain tumor identification and segmentation. The BRATS dataset offers annotated MRI scans that reflect different grades and types of brain tumors; we also selected it for further study. The BRATS dataset, that provides more precise and useful data required to train a model, is extensively used in brain tumor research. Our project's main goal is to create a CNN-based system which can precisely segment the tumor regions in MRI images to determine brain tumor levels in categories like high grade, low grade, and mid grade.

By eliminating manual analysis and helping physicians make better, quicker decisions about how to treat patients, this technology has the potential to increase the speed and accuracy of brain tumor identification. Our study addresses the urgent demand for trustworthy, automated tools in medical diagnostics by focusing on both the classification and segmentation parts.

**Future Work:**

* **Integration with AI for Personalized Medicine**: Future developments may focus on integrating the detection system with AI algorithms that consider genetic, environmental, and lifestyle factors to provide personalized treatment recommendations for patients.
* **Expansion to Other Tumor Types**: The system could be expanded to detect and classify other types of tumors, not just brain tumors, enhancing its applicability in oncology and improving overall cancer care.
* **Improvement of Interpretability and Explainability**: Research can be directed towards developing models that are more interpretable, allowing clinicians to understand the reasoning behind specific predictions. This would foster trust and facilitate better clinical decisions.
* **Mobile and Remote Applications**: The development of mobile applications for healthcare professionals could allow for on-the-go access to the detection system, enabling quicker decisions in emergency situations or remote consultations.

**Appendix A**

**Problem Classification:**

**Image Segmentation (NP-Hard):** Tumor segmentation from MRI scans is NP-hard due to the complexity of isolating tumor, but deep learning models like U-Net provide efficient approximations

**Tumor Classification (NP):** Tumor classification into severity levels is an NP problem, solvable in polynomial time using machine learning models like CNNs, making it computationally feasible.

**Heuristic Solutions for NP-Hard Problems:** Deep learning models serve as heuristics, offering practical approximations to NP-hard tasks like segmentation without needing exact solutions.

**1.** Input Data

* **MRI Image**: An MRI scan is represented as a 2D or 3D matrix: I(x,y,z)where x,y,z are spatial coordinates.I(x, y, z) \quad \text{where } x, y, z \text{ are spatial coordinates}.I(x,y,z)where x,y,z are spatial coordinates.
* **Normalization**: The pixel intensity values I(x,y,z)I(x, y, z)I(x,y,z) are normalized to a range [0, 1] for consistent input.

**2.** Preprocessing

* **Image Smoothing**: Apply Gaussian filter to remove noise:

I′(x,y,z)=I(x,y,z)∗G(x,y,z;σ)I'(x, y, z) = I(x, y, z) \ast G(x, y, z; \sigma)I′(x,y,z)=I(x,y,z)∗G(x,y,z;σ)

* **Image Segmentation**: Using methods like thresholding or U-Net for segmenting the tumor region:

S(x,y,z)=Segmentation Model(I′(x,y,z))S(x, y, z) = \text{Segmentation Model}(I'(x, y, z))S(x,y,z)=Segmentation Model(I′(x,y,z))

where S(x,y,z)S(x, y, z)S(x,y,z) is a binary mask highlighting the tumor.

**3.** Feature Extraction

* **Shape and Texture Features**: Extract features such as tumor size, shape, and texture metrics:
* **Area**: A=∑x,y,zS(x,y,z)A = \sum\_{x, y, z} S(x, y, z)A=∑x,y,z​S(x,y,z)
* **Perimeter**: Calculated using contour detection methods.
* **Texture Features**: Using statistical measures like GLCM (Gray-Level Co-occurrence Matrix).
* **Statistical Measures**: Mean, standard deviation, skewness of pixel intensity values within the tumor region.

**4.** Dimensionality Reduction (e.g., PCA)

* Given a feature vector X∈Rn\mathbf{X} \in \mathbb{R}^nX∈Rn, apply PCA to reduce dimensions: Xreduced=X×W\mathbf{X}\_{\text{reduced}} = \mathbf{X} \times \mathbf{W}Xreduced​=X×W where W\mathbf{W}W is the matrix of principal components.

**5.** Machine Learning Model

**Training a Classifier**: Use a machine learning or deep learning model such as CNN for classification:

Output=f(Xreduced;θ)\text{Output}=f(\mathbf{X}\_{\text{reduced}};\theta)Output=f(Xreduced​;θ)

where fff is the classifier (e.g., softmax function for multiclass classification) and θ\thetaθ represents the model parameters

**6.** Tumor Level Prediction

* **Regression Model**: If predicting tumor grade, use a regression model:

Level=g(X;θ)\text{Level} = g(\mathbf{X}; \theta)Level=g(X;θ)

where ggg is a regression function (e.g., linear regression or neural network).

* **Evaluation Metrics**: Use metrics like Mean Squared Error (MSE) for regression:

MSE=1N∑i=1N(yi−y^i)2\text{MSE} = \frac{1}{N} \sum\_{i=1}^N (y\_i - \hat{y}\_i)^2MSE=N1​i=1∑N​(yi​−y^​i​)2

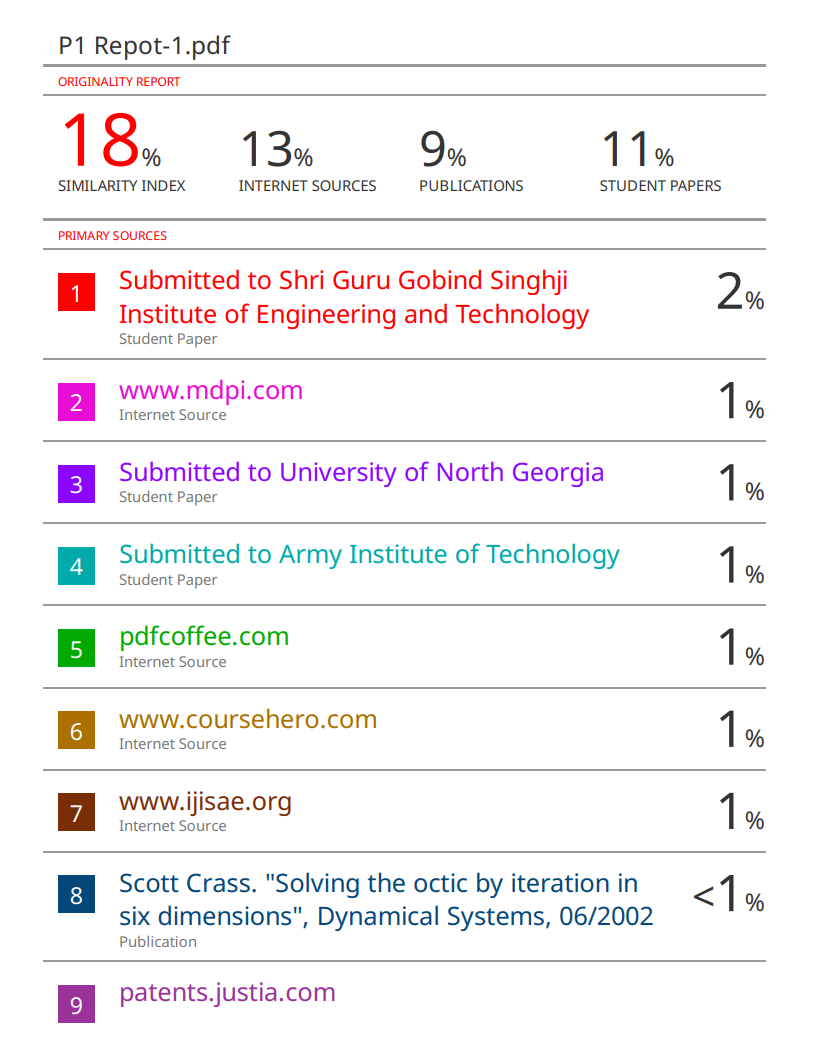
**Appendix B**

1. N Noreen, Sellappan Palaniappan, Abdul Qayyum, Iftikhar Ahmad, Muhammad Imran, and Muhammad Shoaib, “**A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor**,” IEEE March 2020.
2. Hasnain Ali Shah, Faisal Saeed, Sangseok Yun, Jun-Hyun Park, Anand Paul, and Jae-Mo Kang, "**A Robust Approach for Brain Tumor Detection in Magnetic Resonance Images Using Finetuned EfficientNe**t," IEEE March 18, 2022.
3. Wenxin Wang, Zhuo-Xu Cui, Guanxun Cheng, Chentao Cao, Xi Xu, Ziwei Liu, Haifeng Wang, Yulong Qi, Dong Liang, and Yanjie Zhu, "**A Two-Stage Generative Model with CycleGAN and Joint Diffusion for MRI-based Brain Tumor Detection**" IEEE Journal of Biomedical and Health Informatics June 2024.
4. Younis, Q. Li, Z. Afzal, M. J. Adamu, H. B. Kawuwa, F. Hussain, and H. Hussain, "**Abnormal Brain Tumors Classification Using ResNet50 and Its Comprehensive Evaluation**," IEEE June 2024.
5. M. F. Almufareh, M. Imran, A. Khan, M. Humayun, and M. Asim, "**Automated Brain Tumor Segmentation and Classification in MRI Using YOLO-Based**

**Deep Learning**," IEEE Feb 2024.

**Appendix C**

**Plagiarism Report**



**REFERENCES**

1. N Noreen, Sellappan Palaniappan, Abdul Qayyum, Iftikhar Ahmad, Muhammad Imran, and Muhammad Shoaib, “A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor,” IEEE March 2020.
2. Hasnain Ali Shah, Faisal Saeed, Sangseok Yun, Jun-Hyun Park, Anand Paul, and Jae-Mo Kang, "A Robust Approach for Brain Tumor Detection in Magnetic Resonance Images Using Finetuned EfficientNet," IEEE March 18, 2022.
3. Wenxin Wang, Zhuo-Xu Cui, Guanxun Cheng, Chentao Cao, Xi Xu, Ziwei Liu, Haifeng Wang, Yulong Qi, Dong Liang, and Yanjie Zhu, "A Two-Stage Generative Model with CycleGAN and Joint Diffusion for MRI-based Brain Tumor Detection" IEEE Journal of Biomedical and Health Informatics June 2024.
4. Younis, Q. Li, Z. Afzal, M. J. Adamu, H. B. Kawuwa, F. Hussain, and H. Hussain, "Abnormal Brain Tumors Classification Using ResNet50 and Its Comprehensive Evaluation," IEEE June 2024.
5. M. F. Almufareh, M. Imran, A. Khan, M. Humayun, and M. Asim, "Automated Brain Tumor Segmentation and Classification in MRI Using YOLO-Based Deep Learning," IEEE Feb 2024.
6. S. Rajendran, S. K. Rajagopal, T. Thanarajan, K. Shankar, S. Kumar, N. M. Alsubaie, M. K. Ishak, and S. M. Mostafa, "Automated Segmentation of Brain Tumor MRI Images Using Deep Learning" IEEE July 2023.
7. M. Rizwan, A. Shabbir, A. R. Javed, M. Shabbir, T. Baker, and D. Al-Jumeily OBE, "Brain Tumor and Glioma Grade Classification Using Gaussian Convolutional Neural Network" IEEE Mar. 2022.
8. K. Neamah, F. Mohamed, M. M. Adnan, T. Saba, S. A. Bahaj, K. A. Kadhim, and A. R. Khan, "Brain Tumor Classification and Detection Based DL Models: A Systematic Review" IEEE Jan. 2024.
9. Jabbar, S. Naseem, T. Mahmood, T. Saba, F. S. Alamri, and A. Rehman, "Brain Tumor Detection and Multi-Grade Segmentation Through Hybrid Caps-VGGNet Model" IEEE July 2023.
10. Z.Jia and D.Chen, “Brain Tumor Identification and Classification of MRI Images Using Deep Learning Techniques” published in IEEE 2020
11. Sunita Roy, Rikan Saha, Suvarthi Sarkar, Ranjan Mehera, Rajat Kumar Pal, (Member, IEEE), and Samir Kumar Bandyopadhyay, (Senior Member, IEEE), "Brain Tumor Segmentation Using S-Net and SA-Net" IEEE March 2023.
12. Wenqing Li, Wenhui Huang, and Yuanjie Zheng, "CorrDiff: Corrective Diffusion Model for Accurate MRI Brain Tumor Segmentation" IEEE Journal of Biomedical and Health Informatics March 2024.
13. Abdullah A. Asiri, Ahmad Shaf, Tariq Ali, Maryam Zafar, Muhammad Ahmad Pasha, Muhammad Irfan, Saeed Alqahtani, Ahmad Joman Alghamdi, Ali H. Alghamdi, Abdullah Fahad A. Alshamrani, Maqbool Aleylyani, and Sultan Alamri, "Enhancing Brain Tumor Diagnosis: Transitioning from Convolutional Neural Network to Involutional Neural Network" IEEE October 2023.
14. Ji-Hyeon Lee, Jung-Woo Chae, and Hyun-Chong Cho, "Improved Classification of Different Brain Tumors in MRI Scans Using Patterned-GridMask" IEEE March 2024.
15. Sohaib Asif, Wenhui Yi, Qurrat Ul Ain, Jin Hou, Tao Yi, and Jinhai Si, "Improving Effectiveness of Different Deep Transfer Learning-Based Models for Detecting Brain Tumors from MR Images" IEEE February 2022.
16. Xiaoyi Lin, Mingyu Wang, Fei Li, Ziyue Xu, Senior Member, IEEE, Jia Chen, Xin Chen, Member, IEEE, Chenglang Yuan, Songxiong Wu, Yanji Luo, Jingxian Shen, Shi-Ting Feng, and Bingsheng Huang, "Improving Tumor Classification by Reusing Self-Predicted Segmentation of Medical Images as Guiding Knowledge" IEEE March 2024.
17. Saif Ahmad and Pallab K. Choudhury, "On the Performance of Deep Transfer Learning Networks for Brain Tumor Detection Using MR Images" May 2022.
18. Abdullah A. Asiri, Toufique Ahmed Soomro, (Senior Member, IEEE), Ahmed Ali Shah, (Senior Member, IEEE), Ganna Pogrebna, Muhammad Irfan, and Saeed Alqahtani, "Optimized Brain Tumor Detection: A Dual-Module Approach for MRI Image Enhancement and Tumor Classification," IEEE March 2024.
19. Sedat Metlek and Halit Çetiner, "ResUNet+: A New Convolutional and Attention Block-Based Approach for Brain Tumor Segmentation," IEEE July 2023.
20. Ruqsar Zaitoon and Hussain Syed, "RU-Net2+: A Deep Learning Algorithm for Accurate Brain Tumor Segmentation and Survival Rate Prediction" IEEE October 2023.
21. Javaria Amin, Muhammad Sharif, Anandakumar Haldorai, Mussarat Yasmin, and Ramesh Sundar Nayak, "Brain Tumor Detection and Classification Using Machine Learning: A Comprehensive Survey" Complex & Intelligent Systems,November 2022.
22. Xiaoman Zhang, Weidi Xie, Chaoqin Huang, Ya Zhang, Xin Chen, Qi Tian, and Yanfeng Wang, "Self-Supervised Tumor Segmentation with Sim2Real Adaptation" IEEE Journal of Biomedical and Health Informatics September 2023.
23. Dr. R. Cristin, Dr. K. Suresh Kumar, and Dr. P. Anbhazhagan, "Severity Level Classification of Brain Tumor Based on MRI Images Using Fractional-Chicken Swarm Optimization Algorithm" The Computer Journal October 2021.
24. Mohammad Shahjahan Majib, Md. Mahbubur Rahman, (Member, IEEE), T. M. Shahriar Sazzad, Nafiz Imtiaz Khan, and Samrat Kumar Dey, "VGG-SCNet: A VGG Net-Based Deep Learning Framework for Brain Tumor Detection on MRI Images" IEEE Access August 2021.
25. Mohammad Ashraf Ottom, Hanif Abdul Rahman, and Ivo D. Dinov, "Znet: Deep Learning Approach for 2D MRI Brain Tumor Segmentation" IEEE Journal of Translational Engineering in Health and Medicine May 2022.