A Minor Project Report

on

Deep Learning Based Brain Tumor Detection Using YOLOv8

submitted in partial fulfillment of the requirements for the award of degree

Bachelor of Technology

in

Computer Science and Engineering

by

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CERTIFICATE OF APPROVAL

This project work (B9) entitled " **Deep Learning Based Brain Tumor Detection Using YOLOv8** " by Ms. Srija, Registration No. 21211A0592, Mr . Balakrishna, Registration No. 21211A0580, Mr . Abhilash, Registration No. 21211A0586, Mr . Naveen, Registration No. 21211A0571, under the supervision of Mrs. Shilpa in the Department of Computer Science and Engineering, B V Raju Institute of Technology, Narsapur, is hereby submitted for the partial fulfillment of completing Minor Project during II B.Tech II Semester (2022 - 2023 EVEN). This report has been accepted by Research Domain Computational Intelligence and forwarded to the Controller of Examination, B V Raju Institute of Technology, also submitted to Department Special Lab " Artificial Intelligence Machine Learning" for the further procedures.

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DECLARATION

We, the members of Research Group domain **computational Intelligence** under **Artificial Intelligence Machine Learning** special lab , declare that this report titled: **Deep Learning Based Brain Tumor Detection Using YOLOv8** is our original work and has been submitted in whole or in parts for International conference or journal **ICATAS 2023**. All sources of information used in this report have been acknowledged and referenced respectively.

This project was undertaken as a requirement for the completion of our **II B.Tech II Sem Minor project** in Department of **Computer Science and Engineering** at **B V Raju Institute of Technology**, Narsapur. The project was carried out between 31-March-2023 and 11-August-2023. During this time, we as a team were responsible for the process model selection, development of the micro document and designing of the project.

Deep Learning Based Brain Tumor Detection Using YOLOv8. The project involved extensive research on the current segmentation models, identifying the key features required for the segmentation, and developing a prototype. The prototype was then tested and refined to ensure that it met the specified requirements.

We would like to express our gratitude to our project supervisor Mrs.Shilpa for her guidance and support throughout this project. We would also like to thank our Department Head Dr.CH.Madhu babu for his help and efforts. We also thank the Brain Tumor Detection experts for providing valuable insights into the Brain anatomy, which greatly assisted in the development of segmentation model.

We declare that this report represents Our own work, and any assistance received from others has been acknowledged and appropriately referenced.

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Thank you all for your assistance and support.

The experience of working on this project will surely enrich our technical knowledge and also give us hands on experience of working on a project and help develop our team's skill set to a great extent.

ABSTRACT

Early diagnosis and patient treatment are greatly aided by the early detection of brain tumours. In this study, we give a thorough investigation on YOLOv8 model-based deep learning-based brain tumour identification. To train and test our model, we used the BRATS 2022 dataset, which consists of high-resolution brain MRI scans.We used pre-trained weights from the COCO dataset to initialise the YOLOv8 architecture, which improved the performance of our model. This initialization made it possible for our model to use information gleaned from a variety of objects, improving the detection accuracy of brain tumours. Additionally, it made it easier to find tumours of varied sizes and forms, strengthening and expanding the model. Our research's focus on increasing training speed without sacrificing accuracy is one of its major achievements. We significantly cut training time while retaining good detection accuracy by using optimisation approaches including batch normalisation and sophisticated data augmentation methodologies. This development is especially helpful in the medical industry, where prompt and precise diagnosis are crucial.

Keywords: Deep Learning, Brain segmentation, Brain MRI images, YOLOv8 architecture

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LIST OF ACRONYMS AND ABBREVIATIONS

YOLOv8 You Only Look Once

CNN Convolution Neural Network

CSPDarknet Cross Stage Partial Darknet

MRI Magnetic Resonance Imaging

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CHAPTER - 1

1. INTRODUCTION

Brain tumors are a significant and often life threatening medical condition that can be challenging to diagnose and treat. By training deep learning algorithms on large datasets of annotated medical images, researchers have shown that these algorithms can achieve high levels of accuracy in identifying brain tumors by adding new features and enhancements for improved performance, flexibility, and efficiency.

1.1. Background

Deep learning has witnessed recent advancements that have led to a growing interest in using this technology to improve medical image analysis, including the the categorization of brain tumors. Numerous studies have shown that deep learning algorithms can achieve high levels of accuracy in identifying brain tumors based on MRI or CT scans. In recent years, deep learning algorithms have shown promise in improving the accuracy of medical image analysis, including the classification of brain tumors. in this study we used YOLOv8 which expands on the success of earlier editions as a cutting-edge, state-of-the-art (SOTA) model.

1.2. Motivation

The motivation behind the development of Brain Tumor Detection and AI Integration Model stems from the growing importance of leveraging artificial intelligence (AI) and machine learning in the field of tumor detection. MRI images of brain plays a crucial role in diagnosing and planning treatments for various tumor conditions. However, the manual analysis of brain MRI images and the extraction of specific information, such as brain segmentation and predicting tumor type, can be time-consuming and prone to human errors.

The project aims to address these challenges by harnessing the power of AI to automate the brain segmentation process and integrate it with YOLOv8 and Deep Learning methodologies for predicting the brain tumor from the segmented data. By automating the segmentation of brain in MRI images, the model can save valuable time for medical professionals and enhance the accuracy.

1.3. Problem statement

- Previous models take more training speed to overcome this we will be using YOLOv8 technique.
- Existing systems takes more storage space that effects loss of data in future.
- Improving evaluation matrix for detection and classification of BT using YOLOv8, where in previous model using YOLOv5 accuracy and precision is about 89 – 90.

1.4. Objectives

- For transfer learning we are using YOLOv8 with backbone CSDARKNET and Panet.
- Taking Pre-trained weights from cocoa dataset.
- For feature extraction we will be using DARKNET framework which increases the speed of extraction.

1.5. Scope of Project

To gain an insight into the scope of our project, let us first understand what the term scope of a project means in software development, the scope refers to the boundaries and limitations of a project. It also defines the features, functions, and requirements of the software being developed. The scope of a software project describes what the software will and will not do, and what is included and excluded from the project.

The Brain Tumor Detection will consist of two primary functionalities:

The project aims to deliver the following key features:

- Our model for object detection was developed using YOLO V8. YOLOv8 supports a number of backbones, including EfficientNet, ResNet, and CSPDarknet, allowing users to select the model that is suitable for their particular use case.

- Our research involved training multiple variants of the YOLOv8 model, namely YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x. During the training process, we utilized data from 0 to 50 epochs and now aim to evaluate how well our model performs when applied to data with fewer epochs.
- The input images are fed to the backbone, and the FOCUS module splits the input picture into four smaller ones before concatenating them together.

The boundaries and limitations of Brain Tumor Detection can also be defined by its scope, which also outlines the features, functions, and requirements of the system. Some of these boundaries and limitations are:

- **Data Quality and Quantity**: The model's performance heavily relies on the availability and quality of annotated brain MRI images for training. Limited or biased datasets could lead to sub-optimal segmentation and prediction results.
- **Hardware and Computational Resources**:The implementation of deep learning models requires substantial computational resources, particularly for real-time applications. Deploying the model on resource-constrained devices or in low-resource settings might be challenging.
- **Interpretability**:Deep learning models are often considered as black-box models, which means that understanding why they make a specific prediction can be difficult. In a medical context, interpretability is crucial for doctors to trust and act on the model's predictions.
- **Complexity of Brain Structures**: Complexity of Brain Structures.

Addressing these limitations through ongoing research, collaboration with neurologists, and continuous model refinement will be essential for maximizing the model's potential impact on brain treatment planning.

Overall, the project report will provide a comprehensive understanding of the Brain Tumor Detection. The report will serve as a valuable resource for Brain practitioners interested in forensic.

CHAPTER - 2

2. LITERATURE SURVEY

Wang et al. (2019) developed a deep learning algorithm that achieved an accuracy of 91.5While these studies have shown promising results, there is still room for improvement in the accuracy of brain tumor classification using deep learning algorithms. Challenges include the development of algorithms that can accurately differentiate between different types of brain tumors, as well as the generalizability of these algorithms to different populations and imaging modalities.[1]

e, Zhu et al. (2019) developed a recurrent convolutional neural network (RCNN) for brain tumor detection, achieving an accuracy of 96.84Another development in detection of brain tumor classification using deep learning is the development of larger and more diverse datasets. The availability of large, annotated datasets is critical for training deep learning algorithms. Several studies have developed datasets specifically for brain tumor detection, such as the BraTS (Brain Tumor Segmentation) dataset. The BraTS dataset comprises magnetic resonance imaging (MRI) scans collected from 285 individuals diagnosed with brain tumors. , making it One of the most significant datasets available for brain tumor detection. The integration of multiple imaging modalities is another development in deep learning-based brain tumor detection.[2]

Havaei et al. (2017) developed a CNN based algorithm for brain tumor segmentation that integrated information from T1-weighted, T2-weighted, and FLAIR MRI sequences. Despite the significant developments in brain tumor detection using deep learning techniques detection, several challenges and limitations remain. One challenge is the limited availability of annotated medical images. The creation of large, diverse datasets of annotated medical images can be a time-intensive process and expensive process that requires the collaboration of multiple institutions.[3]

e, Kamnitsas et al. (2017) used a pre-trained CNN model for brain tumor segmentation and achieved state-of-the-art results on the BraTS dataset. Another development is the use of attention mechanisms in deep learning algorithms utilized for brain tumor detection. Attention mechanisms allow the model to selectively focus on important regions of the image, improving the accuracy of segmentation and classification tasks.[4]

Wang et al. (2020) proposed an attention-based CNN for brain tumor segmentation that achieved high accuracy on the BraTS dataset. Ensemble learning is another technique that has been extensively studied in deep learning-based brain tumor detection. Ensemble learning involves combining multiple models to enhance the precision and robustness of the predictions. Several studies have shown that ensembling can improve the efficacy of deep learning models in brain tumor detection.[5]

Xu et al. (2020) developed an ensemble of CNNs for brain tumor segmentation that achieved state-of-the-art results on the BraTS dataset. In addition to the technical developments, there has also been a growing emphasis on the clinical translation of brain tumor detection using deep learning algorithms. Several studies have evaluated the performance of deep learning algorithms in clinical settings, demonstrating their potential for assisting clinicians in diagnosis and treatment planning.[6]

, Havaei et al. (2017) developed a CNNbased algorithm for brain tumor segmentation that was able to accurately identify tumor regions in clinical MRI scans. Another important aspect of clinical translation is the integration of deep learning algorithms into existing clinical workflows. This requires careful consideration of the technical and ethical implications, as well as collaboration between researchers, clinicians, and policymakers. Several studies have explored the use of deep learning algorithms in clinical practice, such as the automated triage of emergency room patients with suspected brain tumors.[7]

CHAPTER - 3

3. REQUIREMENT ANALYSIS & SPECIFICATION

This section of the project report is the most critical element as, it provides a foundation for the entire project. It ensures that all stakeholders are aligned on the project's objectives, scope, and deliverables, and it provides a clear road map for the project team to follow.
This section is further divided into 3 sister sections:

- Feasibility Study
- Model Selection
- SRS

3.1. Feasibility Study

A feasibility study is the first stepping stone into the development of any project, including our Brain segmented CNN to predict brain informatics. It involves assessing the potential for the project to be successful, which in turn includes evaluating the market, technology, financial aspects, and operational requirements.

3.1.1. Market Analysis

We perform a small scale analysis of the brain MRI images. The target market for the CNN-based model for brain tumor detection using YOLOv8, Deep Learning.The market for brain tumor detection using YOLOv8 and deep learning is poised for significant growth. With an increasing global incidence of brain tumors and the rapid integration of AI into healthcare, this sector offers promising opportunities. The market is expected to benefit from the demand for accurate and early diagnosis, enhancing patient outcomes. Key players in the healthcare and technology sectors are likely to invest in this niche, while startups specializing in medical imaging AI may also enter the market. Challenges include regulatory compliance, data privacy concerns, and the need for interpretability. However, as AI models improve in accuracy and integration with electronic health records becomes more seamless, the market is anticipated to expand further, catering to both established healthcare systems and emerging markets.

3.1.2. Technology Assessment

As, per our analysis of the market; the technology assessment will evaluate the CNN-based model's accuracy, efficiency, scalability, user friendliness, and compliance with regulations. It will provide valuable insights into the model's suitability for real-world applications in brain tumor detection using deep learning.

3.1.3. Operational Requirements

The operational requirements encompass data acquisition and storage, computing resources, software integration, user training and support, maintenance and updates, data security, scalability, regulatory compliance, backup and disaster recovery, and model explainability. Meeting these requirements will enable the smooth and effective deployment of the CNN-based model brain tumor detection using deep learning.

3.1.4. Financial Analysis

the financial analysis will assess the initial investment, development and training costs, operational expenses, revenue generation, ROI, break-even point, cost-benefit analysis, competitive pricing, risk assessment, and long-term financial projections. The analysis will provide crucial insights into the financial viability and potential profitability of the CNN-based model which extends to forensic.

3.1.5. Risk Assessment

A comprehensive risk assessment for the CNN-based model should address data quality, overfitting, regulatory compliance, security, model explainability, hardware failures, user errors, market competition, technology landscape changes, ethical considerations, cost overruns, and user acceptance. Proactively identifying and mitigating these risks will enhance the model's effectiveness and long-term success in brain tumor detection.

3.2. Selection of Process Model

The software life cycle process model is a framework that outlines the various stages involved in the development of a software application. So, choosing a life cycle process model is the stepping stone into the development of a software product.

3.2.1. Process Models

The choice of software development process model for brain tumor detection and future integration of a CNN model for prediction using Deep Learning,CNN an iterative and flexible process model would be suitable. One such process model that fits well with AI and deep learning projects is the Agile methodology.

3.2.2. Why Agile

Here are some reasons why the Agile model is the best choice for developing brain segmentation model:

- **Adaptability to Changing Requirements:** In AI projects, requirements and objectives can evolve rapidly due to advancements in technology or new insights from stakeholders. The Agile model's iterative and incremental approach allows you to adapt to these changes easily, ensuring that your project stays aligned with the latest developments and meets evolving needs.
- **Faster Time-to-Value:** Agile's short development cycles, known as sprints, enable you to deliver working components of the project in a timely manner. This means you can start utilizing and validating the brain segmentation and AI models early on, providing value to brain testing professionals and researchers sooner than traditional development approaches.
- **Continuous Stakeholder Engagement:** Agile emphasizes regular interactions with stakeholders, including brain tumor detection experts, data scientists, and end-users. This continuous engagement ensures that their feedback and insights are incorporated into the project throughout its lifecycle, resulting in a solution that truly addresses their needs and expectations.
- **Risk Mitigation and Early Issue Identification:** Agile's iterative nature allows for frequent testing and validation of the brain segmentation and AI models. This early and regular testing helps in identifying potential issues and risks early on in the development process. Addressing these issues promptly minimizes the chances of costly and time-consuming problems later in the project, leading to a more successful and efficient implementation.

3.2.3. Why Not

Every coin has two sides thus, we can't forget to consider that the waterfall model has some limitations too such as:

- Scope Management Scope management for brain tumor detection using YOLOv8 and deep learning involves defining project objectives, constraints, and tasks. Begin with clear objectives, specifying the desired outcomes and constraints like budget and time. Define the scope of data collection, model development, and performance evaluation. Tasks should include data preprocessing, YOLOv8 model training, and testing. Ensure stakeholder involvement to align expectations and consider legal and ethical aspects like patient data privacy. Develop a communication plan and risk management strategy. Allocate resources effectively, and document the project for future reference. Continuously monitor and control scope to stay within the defined boundaries, preventing scope creep and ensuring project success.

- Resource Intensive Brain tumor detection with YOLOv8 and deep learning is resource-intensive due to several factors. Firstly, the training of deep learning models like YOLOv8 demands substantial computational power, typically requiring high-end GPUs or specialized hardware. The datasets used for training and validation can be massive, necessitating ample storage capacity. Data preprocessing, including resizing and normalization, adds to computational demands. Model training itself is time-consuming, often taking days or weeks, depending on factors like dataset size and model complexity. Hyperparameter tuning and experimentation further consume resources. Maintaining a suitable infrastructure with GPU servers or cloud resources is essential but costly. Skilled personnel are required for model development and fine-tuning, adding to project expenses. Additionally, energy consumption is high during intensive computation, which impacts operational costs and environmental concerns. Scalability and real-time processing increase resource requirements, as do rigorous quality assurance and testing procedures.

While Agile offers many benefits, it may not be suitable for projects with fixed, rigid timelines or highly regulated environments, where extensive documentation and upfront planning are mandatory. In such cases, adopting Agile might require careful planning and adaptation to address the specific needs and constraints of the project.

3.3. Software Requirements Specification

3.4. Introduction

Brain tumors are a significant and often life threatening medical condition that can be challenging to diagnose and treat. Accurate and timely identification of brain tumors is critical for patient outcomes, as early detection can lead to more effective treatment options and better prognoses. Currently, radiologists rely on visual interpretation of medical images, such as MRI or CT scans, to identify brain tumors. However, this method is subject to human error and can be time-consuming. In recent years, deep learning algorithms have shown promise in improving the accuracy of medical image analysis, including the classification of brain tumors. The whole spectrum of visual AI tasks, including as detection, segmentation, posture estimation, tracking, and classification, are supported by YOLOv8. Because of its adaptability, YOLOv8 can be used in a variety of contexts and applications.For neural network models, it is common practise to use pretrained features on data. On the Brats 2022 annotated dataset, we used YOLOv8's various variant approach in this study to locate brain tumours. Our model for object detection was developed using YOLO V8. YOLOv8 supports a number of backbones, including EfficientNet, ResNet, and CSPDarknet, allowing users to select the model that is suitable for their particular use case. We used the YOLO V5 model, which was calibrated using the COCO dataset. This model was successfully trained using our annotated MRI images using roboflow. The foundation of YOLOv8 is a modified version of the CSPDarknet53 architecture. 53 convolutional layers make up this design, which also uses cross-stage partial connections to enhance information transfer between the various layers. A number of convolutional layers and a string of fully connected layers make up the head of the YOLOv8 algorithm. .All YOLOv5 model iterations have been utilised for diagnosis of brain tumours. For the YOLOv8s, YOLOv8n, YOLOv8m, YOLOv8l, and YOLOv8x models, respectively, the accuracy is 90.2.

3.4.1. Purpose

The purpose of this document is to define the requirements and specifications for the development of the Brain Tumor Segmentation and AI Integration Model. The model aims to automate the segmentation of brain in MRI images and further use the segmented data to find the brain tumor using Convolutional Neural Networks (CNN).

3.4.2. Scope

Deep Learning Based Brain Tumor Detection using YOLOv8 will include the following functionalities:

- Brain Segmentation: The model will take dental MRI images as input and perform brain segmentation to create binary masks of the segmented brain.
- Brain Tumor Prediction: The segmented brain data will be used as input to a CNN YOLOv8 model to predict the brain tumor detection.

3.4.3. Definitions, Acronyms and Abbreviations

- **Definitions:**
  CNN: Convolutional Neural Network
  AI: Artificial Intelligence
  YOLOv8: You Only Look Once
  SRS: Software Requirements Specification

- **Acronyms:**
  MRI: Magnetic Resonance Imaging
  ROI: Region of Interest
  FCN: Fully Convolutional Network
  IoU: Intersection over Union
  GUI: Graphical User Interface

- **Abbreviations:**
  CNN: Convolutional Neural Network
  AI: Artificial Intelligence
  YOLOv8: You Only Look Once
  SRS: Software Requirements Specification

3.4.4. References

IEEE Std 830-1998, IEEE Recommended Practice for Software Requirements Specifications.

3.4.5. Overview

The document will mostly consist of two parts:

- Overall Description

- Specific Requirements

Overall description describes the major components of the system, assumptions and dependencies of the system, while specific requirements describes the functions of the system and their roles in the system and the constraints faced by the system.

3.5. Overall Description

3.5.1. Product Perspective

The Brain Tumor Detection Model will be a self-contained software system that consists of two main parts: the brain segmentation module and the CNN-based brain tumor prediction module. The brain segmentation module will take brain MRI images as input and output binary masks representing the segmented brain. The CNN module will take these segmented brain data as input and brain tumor detection.

3.5.2. Product Functions

The main functions of the Brain Segmentation and Tumor Detection Model are as follows:

- **Brain Segmentation:** The model shall accept brain MRI images as input and perform brain segmentation using a CNN-based approach. The output shall be binary masks representing the segmented brain MRI in the input image.
- **Brain Tumor Detection:** The segmented brain data shall be fed into a CNN model for brain tumor detection. The CNN shall be capable of predicting the tumor detection of the brain using MRI images.

3.5.3. User Characteristics

The intended users of the Brain Segmentation and AI Integration Model are brain tumor detection professionals and researchers. They should have basic technical knowledge to interact with the model and understand the predicted results.

3.5.4. Constraints

The following constraints are considered for the development of the model:

- **Availability of Sufficient Training Data:** The model assumes access to a diverse and representative dataset of brain MRI images for training and validation.
- **Computational Resources:** Adequate computational resources, including GPUs, are assumed for training and inference.

3.5.5. Assumptions & Dependencies

The Brain Segmentation and AI Integration Model assumes the following:

- Availability of labeled brain MRI images for training the brain segmentation model and for evaluating the tumor in the brain.
- Availability of suitable hardware resources for model training and inference.
- Availability of relevant libraries and frameworks for implementing the brain segmentation and CNN models.

3.6. Specific Requirements

3.6.1. External Interfaces

The Brain Segmentation and AI Integration Model may include the following external interfaces:

- User Interface (if applicable): The model may have a graphical user interface (GUI) to allow users to interact with the system, upload brain MRI images, view the segmented results, and access the tumor detection results.
- Data Input Interface: The model shall accept brain MRI images as input for brain segmentation and provide the predicted brain tumor as output.

3.6.2. Functions

The primary functions of the Brain Segmentation and AI Integration Model are:

- **Brain Segmentation:** The model shall accept brain MRI images as input and perform brain segmentation using a CNN-based approach. The output shall be binary masks representing the segmented brain in the input image.

- **Brain Prediction:** The segmented brain data shall be fed into a CNN model for brain tumor detection. The CNN shall be capable of predicting the brain tumor detection using Deep Learning.

3.6.3. Performance Requirements

The Brain Segmentation and AI Integration Model shall meet the following performance requirements:

- **Brain Segmentation Accuracy:** YOLOv8 is incredibly accurate in detecting objects and segments in an image, and its MAP (mean average precision) score is up to 44 percentage higher than other state-of-the-art models like Detectron2, with an mAP of 63.2 percentage on the COCO dataset.
- **Brain Tumor Prediction Accuracy:** In YOLO variation, we were able to reach an accuracy of 92.2 percent, with the YOLOv8l model providing us with the highest accuracy compared to the YOLOv8n and YOLOv8s models.

3.6.4. Logical Database Requirements

The Brain Segmentation and AI Integration Model do not require a logical database as it does not involve persistent data storage.

3.6.5. Design Constraints

The design constraints of the Brain Segmentation and AI Integration Model include:

- **Model Size:** The model should be designed with consideration for deployment on various platforms, including devices with limited computational resources.
- **Real-time Processing:** The model should aim to provide real-time or near real-time processing for brain segmentation and brain tumor detection prediction tasks.
- **Compatibility:** The model should be compatible with commonly used brain MRI image formats and input data types for seamless integration with brain imaging systems.

3.6.6. Software System Quality Attributes

The quality attributes of the Brain Segmentation and AI Integration Model include:

- **Accuracy:** The model should provide accurate brain segmentation and reliable brain tumor predictions based on the input MRI images.
- **Performance:** The model should demonstrate efficient performance in terms of processing speed and resource utilization.
- **Robustness:** The model should be able to handle variations in input MRI images, such as different resolutions and orientations.
- **Usability:** If applicable, the model's user interface should be intuitive and user-friendly for brain tumor detection professionals and researchers.
- **Security:** The model should ensure the confidentiality and privacy of patient data if it interacts with sensitive information.

3.6.7. Object-Oriented Models

The Brain Segmentation and AI Integration Model can be represented using object-oriented models with the following key components:

- **ImageProcessor Class:** Responsible for pre-processing dental MRI images and feeding them into the brain segmentation model.
- **SegmentationModel Class:** Implements the brain segmentation CNN model and returns the binary masks for segmented brain.
- **CNN Model Class:** Implements the CNN-based brain tumor prediction model, taking the segmented brain data as input and returning brain tumor predictions.

3.6.8. Appendices

1. Glossary

- MRI: A type of Magnetic Resonance Imaging used for imaging brain structures.
- CNN: Convolutional Neural Network, a type of deep learning model for structured data.
- CSPDarknet53: 53 convolutional layers make up this design, which also uses cross-stage partial connections to enhance information transfer between the various layers. A number of convolutional layers and a string of fully connected layers make up the head of the YOLOv8 algorithm.

2. References IEEE Std 830-1998, IEEE Recommended Practice for Software Requirements Specifications.

CHAPTER - 4

4. DESIGN SPECIFICATION

The design specification of a Brain Tumor segmented CNN involves identifying the requirements and functionalities of the system to be developed. In this section of the report we complete this very task by developing different diagrams.

The system should have an intuitive and user-friendly interface that is easy to use for neurologists. The system should be designed to handle complex shapes of brain and should be scalable to accommodate growth in the number of brain segmentations.

The system should also be designed to integrate with other systems such as brain tumor detection and analysis.

We understand all these requirements better by developing the following diagrams of our system:

- Use Case Diagram
- Data Flow Diagram
- Class Diagram
- Sequence Diagram
- Activity Diagram
- State Chart Diagram

4.1. Usecase Diagram

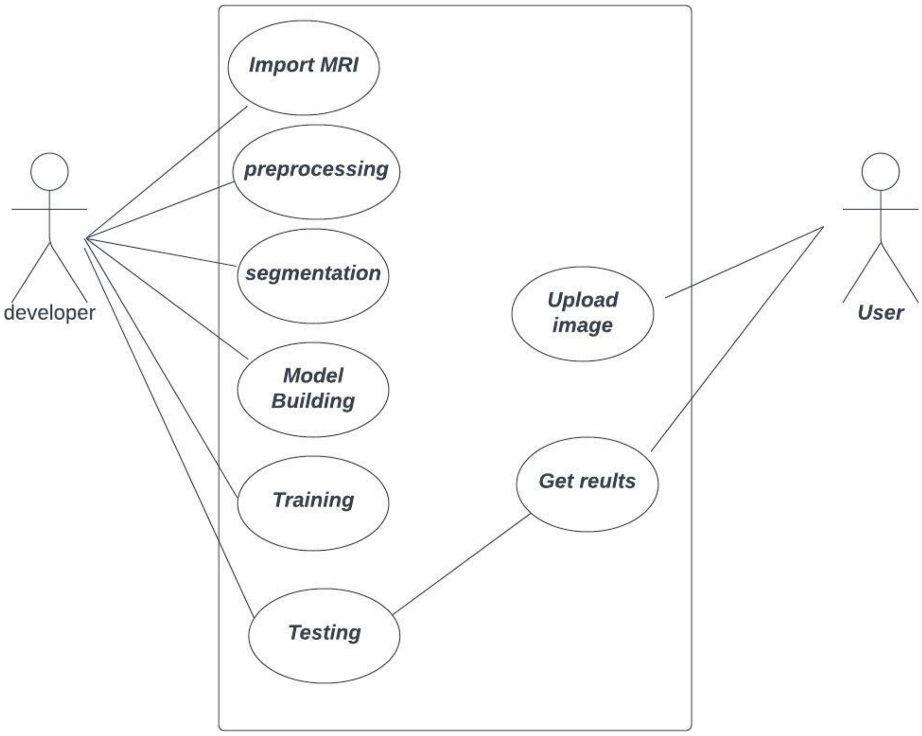


Figure 4.1: Usecase Diagram of Table Tech.

4.2. DFD Diagram

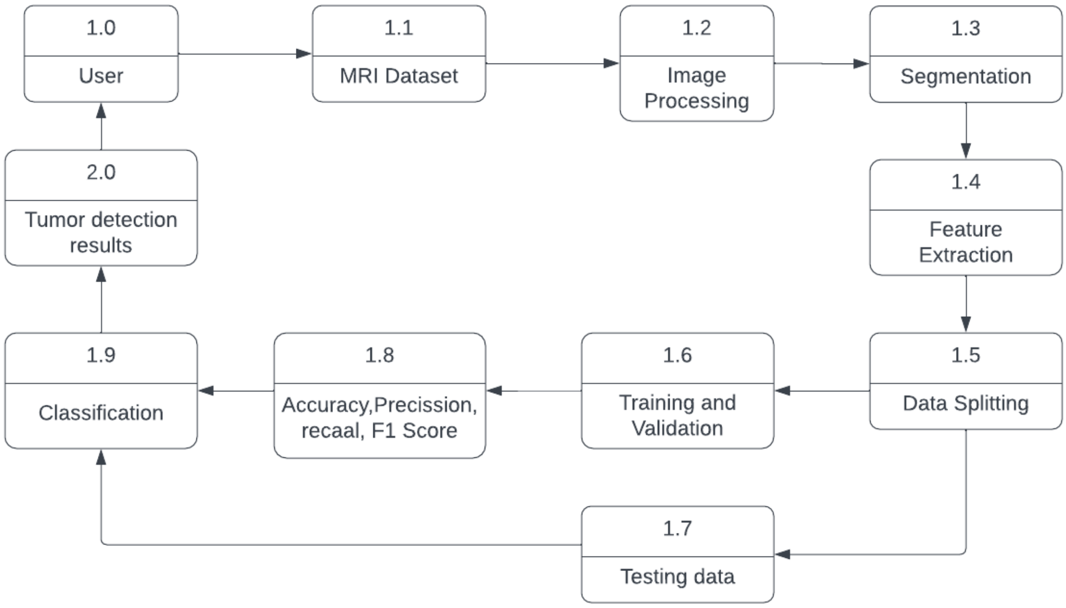


Figure 4.2: DFD Diagram of Table Tech.

4.3. Class Diagram

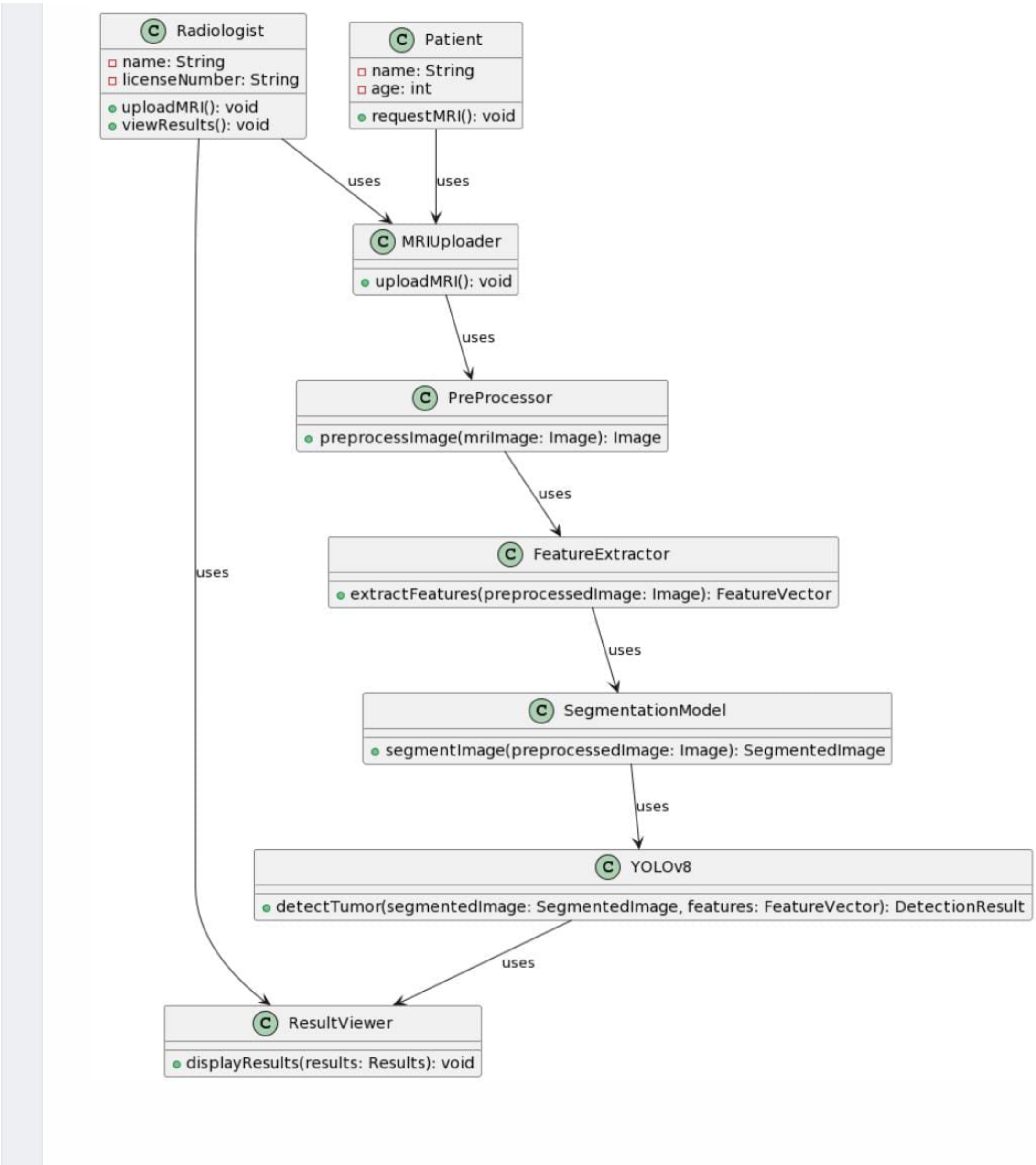


Figure 4.3: Class Diagram of Table Tech.

4.4. Sequence Diagram

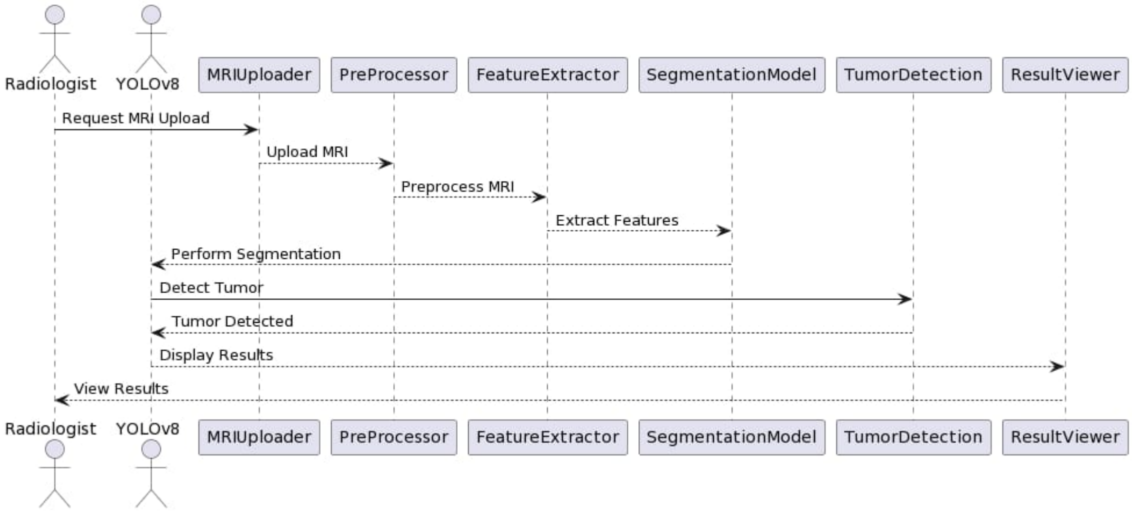


Figure 4.4: Sequence Diagram of Table Tech.

4.5. Activity Diagram

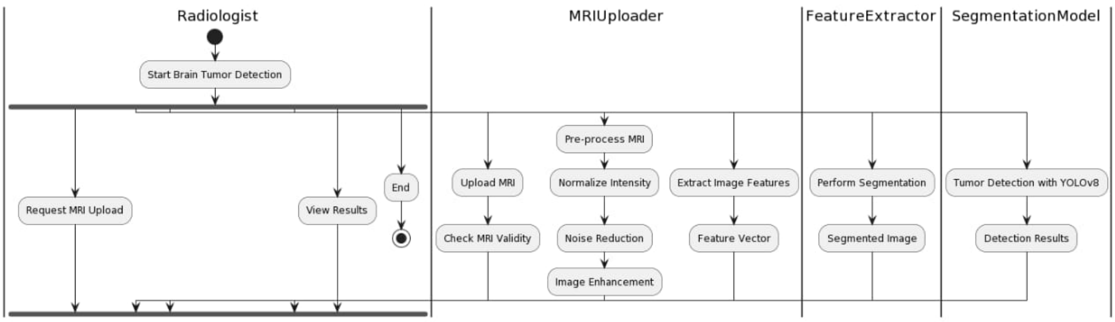


Figure 4.5: Activity Diagram of Table Tech.

4.6. Statechart Diagram

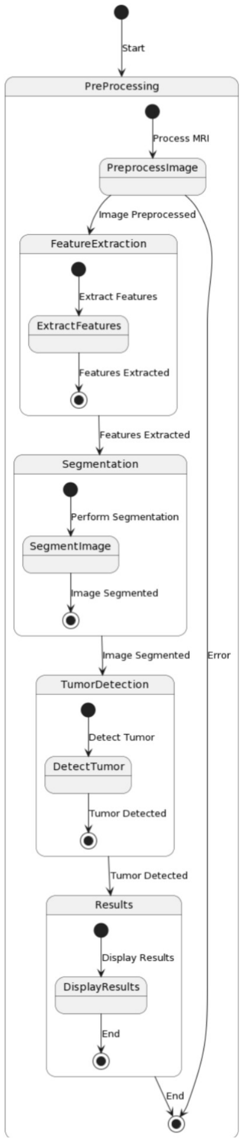


Figure 4.6: Statechart Diagram of Table Tech.

CHAPTER - 5

5. METHODOLOGY

5.1. Modules

Data collection : MRI images with Brats2022 dataset.

Data preprocessing: Techniques used – Image sizing, image normalization, image segmentation.

Data Augmentation: Techniques used - GAN-based augmentation.

Splitting dataset module: 80/20, 80% - training, 20%- testing.

Training: Training dataset using YOLOv8: CSP Darknet, Validation.

Evaluation metrics: mAP, accuracy, F1 score, Precision-recall.

Testing: Testing dataset with fine-tuned YOLOv8.

5.2. System Block Diagram

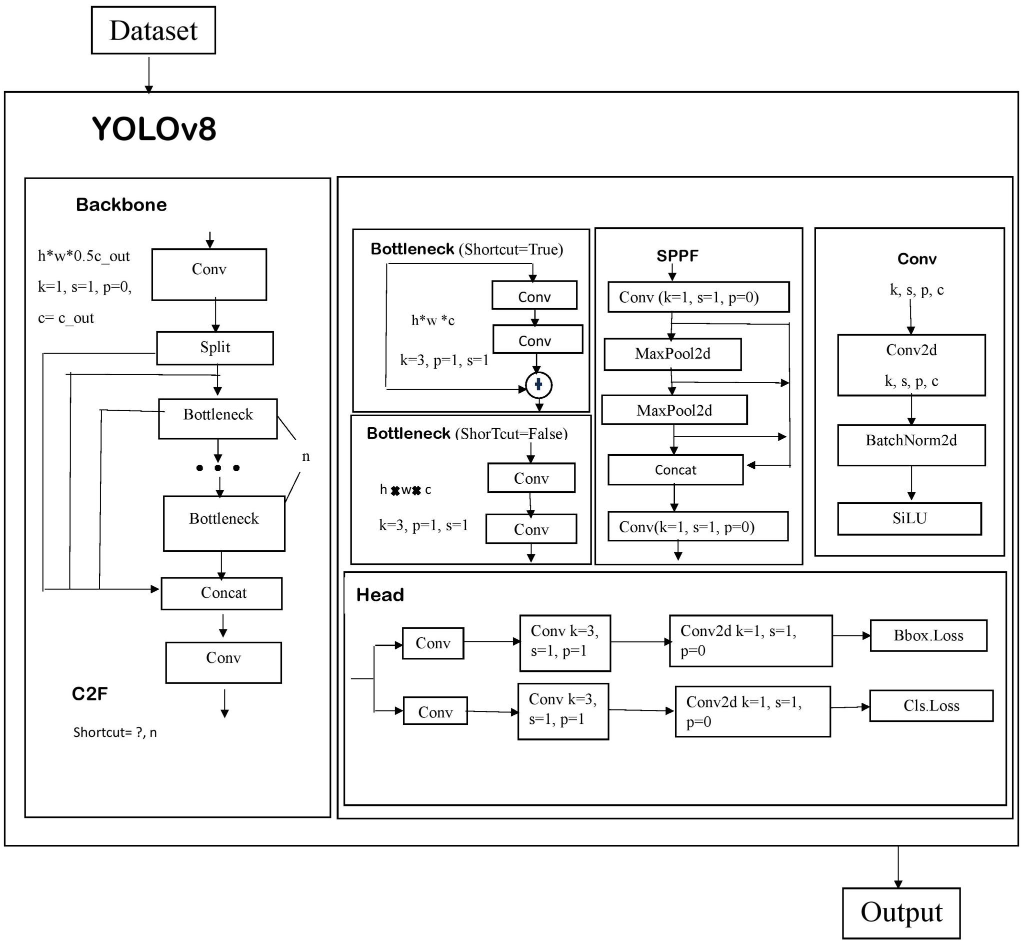


Figure 5.1: System Block Diagram of Table Tech.

CHAPTER - 6

6. IMPLEMENTATION DETAILS

A Brain segmented CNN is a computerized solution that simplifies segmentation of brain. It's main function is to automate the segmentation process because of brain tumor identification and segmentation. It is used to manage tasks such as contour tracing, procrustes analysis and quality improvisation. Further in this section we talk about the implementation details to consider when developing brain tumor segmented CNN.

6.1. Technology Stack

The technology stack for the Brain Tumor Segmentation and AI Integration Model may include Python as the primary programming language for its rich ecosystem of AI and machine learning libraries. Deep learning frameworks like TensorFlow or PyTorch can be utilized to build and train Convolutional Neural Networks (CNN) and Recurrent Convolutional Neural Networks (RCNN) for brain segmentation and tumor prediction. OpenCV can handle image processing tasks on brain MRI images. Convolution neural network libraries like TensorFlow or PyTorch Geometric can be employed for CNN operations. Data visualization can be done with Matplotlib or Seaborn. Flask or Django can be used for web-based user interaction, and HTML/CSS/JavaScript can design the UI. Data can be managed using Google's Big Query or other suitable DBMS, while cloud platforms like Google Cloud Platform or AWS can host the model for scalability and cost-effectiveness.

6.2. System Architecture

While making a decision about the architecture of our system we need to make sure that the system efficiency doesn't decrease in any way. So, we decided to develop Brain Tumor segmented CNN with a scalable and maintainable architecture that should be able to handle large amounts of data and traffic. A common architecture for such systems is the YOLOv8 architecture, it utilizes a CSPDarknet53 backbone and includes features like anchor-based object detection and efficient training techniques for real-time object detection tasks.

6.3. User Interface

The user interface of Brain Segmented CNN will be user-friendly and intuitive. It will allow neurologists to segment the image of a brain quickly and easily, while also allow to detect the tumors efficiently.
The user interface will not require a lot of technical acumen so that professionals of tumor detection are comfortable with such a user interface with minimal complexities.

6.4. Integration

The Brain Segmentation will require seamless integration between the brain segmentation model and the brain tumor prediction model. The segmented brain data generated by the segmentation model will serve as input to the CNN-based prediction model. Additionally, the system will be integrated into a user-friendly web interface using Flask or Django, allowing users to upload dental MRI images for analysis. Cloud deployment will be employed to host the integrated model for accessibility and scalability. During integration, testing and user feedback will be crucial to refine the model and ensure compatibility with various brain MRI image formats and use cases.

6.5. Security

Security is a critical part of our model. The system should be designed to prevent unauthorized access to data and to protect sensitive information such as person's identity.

6.6. Testing and Deployment

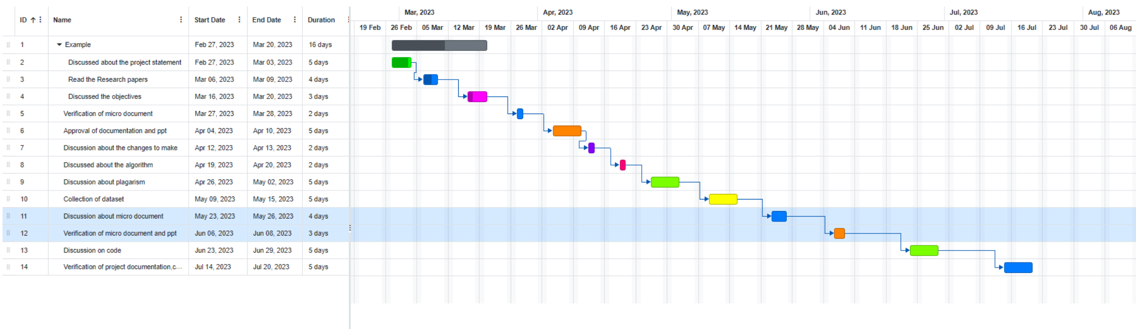
Brain segmented CNN will undergo rigorous testing in line with our Minor project curriculum; these tests will help us ensure that our model meets the functional and performance requirements as mentioned in the problem statement. We can also use continuous integration and deployment practices to streamline the development and deployment process.

Taking all the subsections into consideration, we were successfully able to develop a robust and efficient brain segmentation model Brain Tumor segmented CNN that can streamline segmentation operations, reduce the manual work and enhance applications in various dental fields.

CHAPTER - 7

7. OBSERVATIONS

7.1. Time Domain - Gann Chart



ID	Name	Start Date	End Date	Duration
1	Example	Feb 27, 2023	Mar 20, 2023	16 days
2	Discussed about the project statement	Feb 27, 2023	Mar 03, 2023	5 days
3	Read the Research papers	Mar 06, 2023	Mar 09, 2023	4 days
4	Discussed the objectives	Mar 16, 2023	Mar 20, 2023	3 days
5	Verification of micro document	Mar 27, 2023	Mar 28, 2023	2 days
6	Approval of documentation and ppt	Apr 04, 2023	Apr 10, 2023	5 days
7	Discussion about the changes to make	Apr 12, 2023	Apr 13, 2023	2 days
8	Discussed about the algorithm	Apr 19, 2023	Apr 20, 2023	2 days
9	Discussion about plagarism	Apr 26, 2023	May 02, 2023	5 days
10	Collection of dataset	May 09, 2023	May 15, 2023	5 days
11	Discussion about micro document	May 23, 2023	May 26, 2023	4 days
12	Verification of micro document and ppt	Jun 06, 2023	Jun 08, 2023	3 days
13	Discussion on code	Jun 23, 2023	Jun 29, 2023	5 days
14	Verification of project documentation,c...	Jul 14, 2023	Jul 20, 2023	5 days

Figure 7.1: Gantt Chart.

7.2. Results and Comparitive Study

Our research involved training multiple variants of the YOLOv8 model, namely YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x. During the training process, we utilized data from 0 to 50 epochs and now aim to evaluate how well our model performs when applied to data with fewer epochs. Initially, all the models exhibited relatively low accuracy rates, but as the number of epochs increased, the accuracy rates improved.

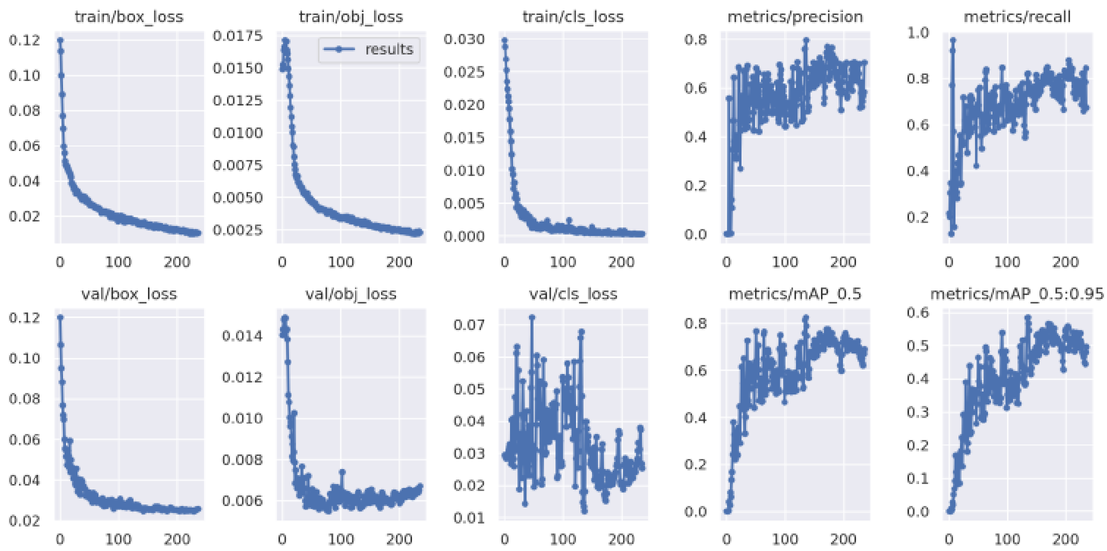


Figure 7.2: Accuracy Curves for YOLOv8s,YOLOv8m,YOLOv8l

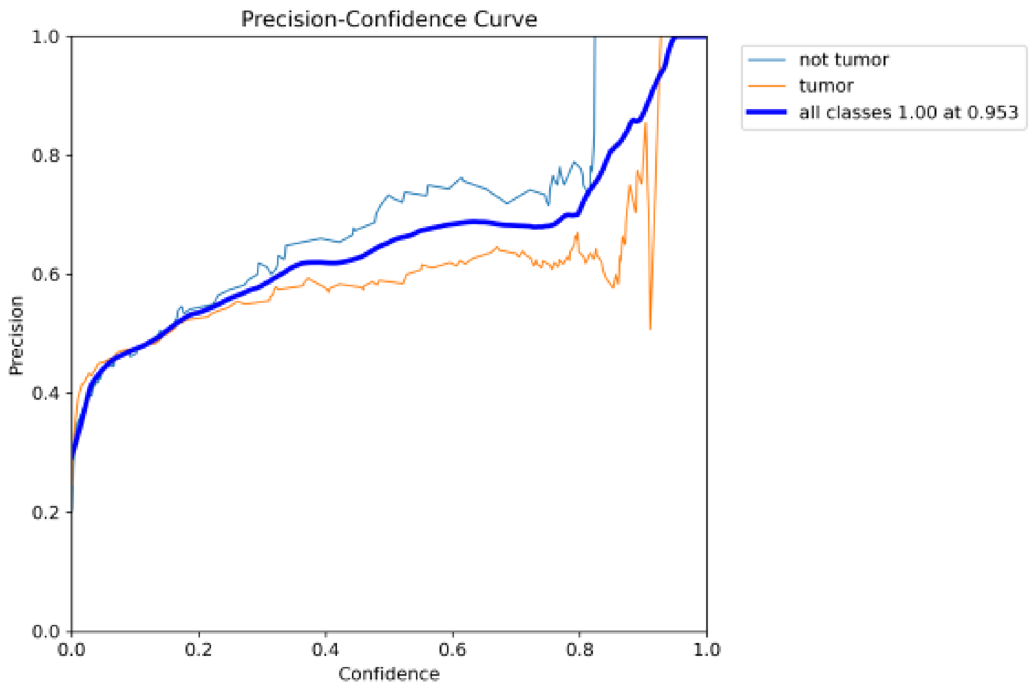


Figure 7.3: Precision-Confidence Curves

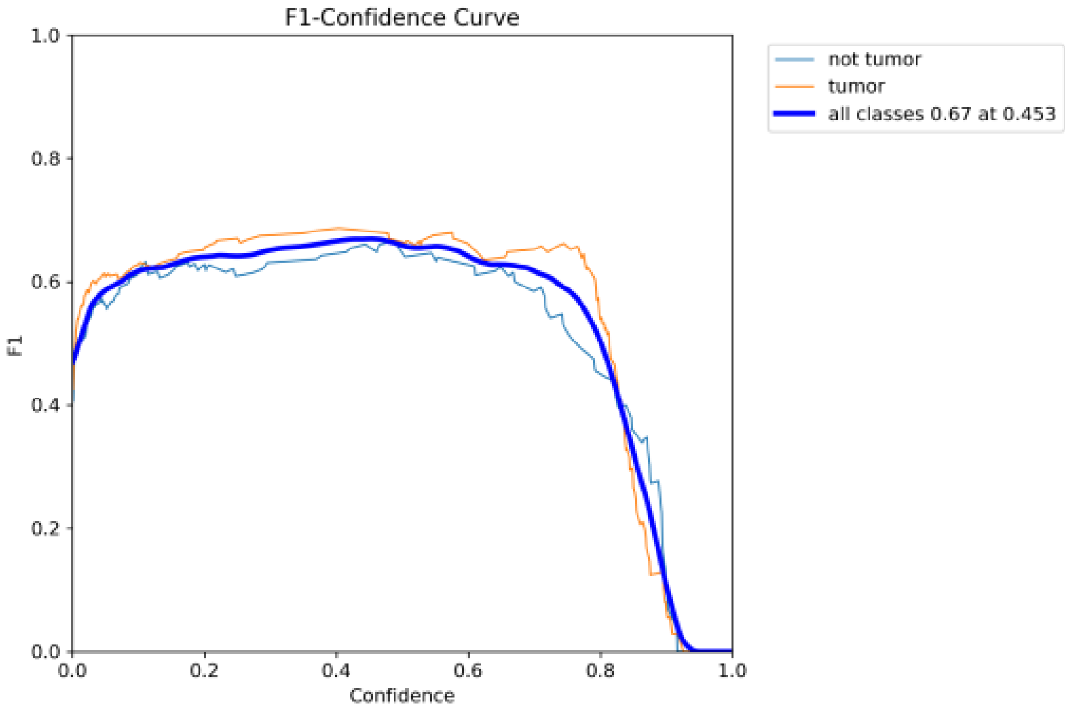


Figure 7.4: F1-Confidence Curves

Table 7.1: YOLOv5 comparision analysis.

	Model	Weight	Precision	Time(min)	Recall	mAP
0	YOLOv8s	15mb	85.9	50.5	85.9	90.2
1	YOLOv8n	10mb	83.5	48	82	90.5
2	YOLOv8m	35mb	87.2	49.3	90.4	91.8
3	YOLOv8l	75mb	90.2	50.2	91.2	91.5
4	YOLOv8x	140mb	93.1	60	92.4	94.2

CHAPTER - 8

8. CONCLUSION

Brain Segmented CNN provides numerous benefits in brain diseases detection applications. By automating various processes :

- Segmentation of brain
- Brain Tumor Detection

Neuro-oncology department can use this segmentation model for further brain tumor detection which will reduce errors and manual work increasing time efficiency.

In the development of this project report, we have successfully worked as a team and as a team, we actually grasped the concepts of computer intelligence and the tasks that come hand in hand with the development of a model. The development stage helped us understand real world implications of the umbrella activities that come under a computer intelligence process model. All in all, the opportunity has allowed us to understand the importance of making documentation while developing a deep learning model.

Our system hasn't yet been tested and evaluated in a real-world neuro oncology department setting but we are very sure that the results will show that it can significantly improve the efficiency of teeth segmentation, reduce errors, and increase accuracy. Overall, our brain segmented CNN for brain tumor detection is a valuable tool for neurologists and neuro-oncologists who are looking to automating brain tumor detection methods.

CHAPTER - 9

9. LIMITATIONS AND FUTURE ENHANCEMENTS

9.1. Limitations

This project is highly planned and acted upon from the beginning. Nevertheless, the project had to face some of the limitations due to various factors. Different aspects of the projects such as nature of data, visualisation methods, data storage method and so on have their own limitations. Some of the limitations faced by the project are:-

1. Implementing deep learning models can be complex, especially for individuals with limited experience in this area. Ensuring proper model architecture, hyperparameter tuning, and training can be time-consuming and require expertise.

2. Preparing the brain MRI data for training, including data cleaning, normalization, and augmentation, can be demanding. Inadequate preprocessing may lead to suboptimal model performance.

3. Training deep learning models on large datasets demands significant computational power.

4. Preventing overfitting is crucial to ensure that the model generalizes well to unseen data. Regularization techniques and careful validation are necessary to mitigate this issue.

5. Maintaining version control and deploying updated versions of the model to production systems can be complex. Proper testing and rollback strategies must be in place to ensure smooth deployments.

6. Ensuring that the model can run efficiently on target hardware, such as brain imaging machines or edge devices, may require optimization and adaptation.

7. Dealing with sensitive medical data necessitates strict adherence to data security and privacy regulations. Implementing secure data storage and access control measures is essential.

8. The success of the model relies on user acceptance and proper training for neuro practitioners

and staff. User-friendly interfaces and comprehensive training materials are vital for successful adoption.

9. Continuous maintenance and support are necessary to address issues, update the model, and provide technical assistance to users.

9.2. Future Enhancements

Future enhancements for the Brain Segmentation and AI Integration Model can be planned to further improve its capabilities and address emerging needs. Some potential areas for enhancement include:

1. Integrate tumor detection and classification capabilities into the model. By identifying common brain conditions like brain activities and thoght process, brain diseases, or abnormalities, the system can assist in early diagnosis and treatment planning.

2. Optimize the model for real-time inference on edge devices or dental imaging machines. This improvement would enable immediate feedback to dentists during examinations, improving the overall clinical workflow.

3. Extend the model to handle various brain imaging modalities, such as magnetic resonace imaging, scans. This expansion would provide a more comprehensive analysis of brain conditions and also helps in finding the type of the brain tumor.

4. Develop a cloud-based platform where neuro professionals can securely upload and share brain images for remote consultations and collaboration. This feature would facilitate the interdisciplinary cooperation.

5. Develop a mobile application that enables neurologists to access the segmentation results and AI predictions on their smartphones or tablets, increasing accessibility and convenience.

6. Implement methods to explain and interpret the model's decisions, helping dentists understand how the AI arrived at specific segmentation results or predictions.

7. Collaborate with brain research institutions to validate and benchmark the model's performance on large-scale datasets and ensure its efficacy in diverse clinical scenarios.

A. APPENDIX

References

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A.1. Project Timeline

Deep Learning Based Brain Tumor Detection Using YOLOv8 project timeline: 31 March 2023 to 11 August 2023