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TumorXtract

Detection & Segmentation

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Abstract

The development of aberrant brain cells, some of which may become cancerous, is known as a brain tumor. The quality of life and life expectancy of patients are enhanced by early and timely illness identification and treatment plans. MRI scans are the most common approach for finding brain tumors. However, the ability of radiologists and other clinical experts to identify, segment, and remove contaminated tumor regions from MRI images is a critical factor in a process that is iterative and labor-intensive and relies on those abilities in these areas. It is difficult to find abnormal brain regions using simple imaging methods. Over the last several years, interest in the machine learning field of deep learning has grown significantly and has been shown to be an effective technique for many challenging issues.

Our project demonstrated how modern deep learning techniques, particularly Convolutional Neural Networks (CNNs), could be utilized to perform detection and segmentation for brain tumors. Unlike other studies that often use smaller or lower-quality datasets, our approach leveraged a large, high-quality, pre-processed dataset, combined with advanced data augmentation and overfitting prevention techniques, to build a robust and highly accurate model. Our models were trained on the Brain Tumor MRI Dataset, a comprehensive collection combining data from the figshare, SARTAJ, and Br35H sources, which provided a rich foundation for both detection and segmentation tasks.

This project culminated in the development of a secure, web-based platform featuring role-based access for clinicians and the ability to generate detailed PDF reports from the AI analysis. Thus, the goal of our project was the automatic detection of brain tumors at an early stage, which can be crucial for improving diagnosis and survival rates. By using these advanced detection and segmentation approaches, we aimed to make a significant contribution to early brain tumor detection and treatment.

Contents

Chapter 1

Introduction

1.0 Introduction

What is Cancer?

Cancer is a significant health concern worldwide, impacting millions of lives. According to data from SEER Cancer Statistics, cancer incidence and mortality rates vary by tumor type, age group, and other factors. Brain and nervous system tumors are among the most complex cancers, requiring precise detection and treatment strategies.

Brain tumor incidence trends from 2000 to 2021 show that:

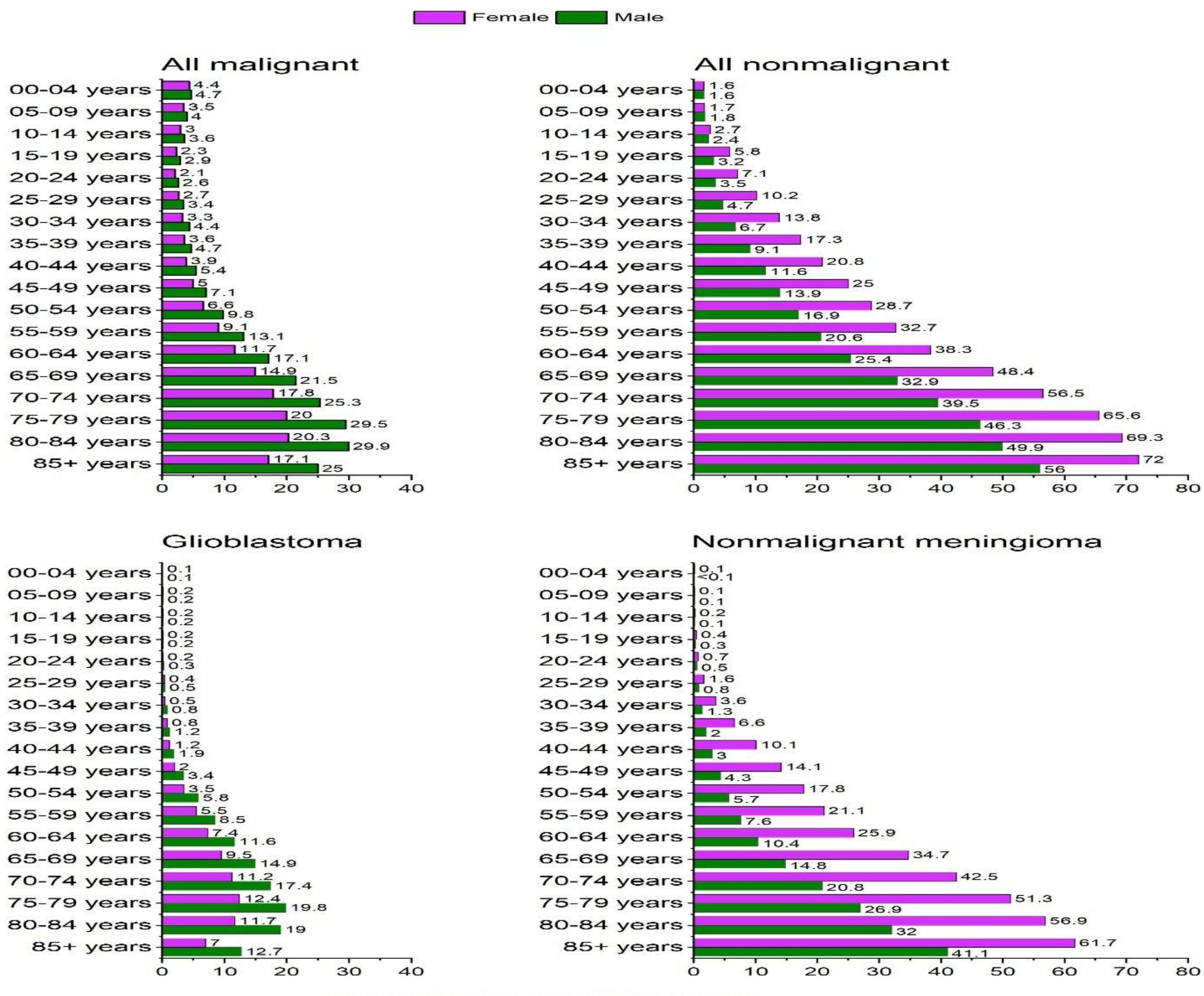

Fig 1.**Error! No text of specified style in document.**.1Distribution of male rates and female rates by age of cases per year

Malignant tumors have relatively stable incidence rates, with males showing slightly higher rates than females. Non-malignant tumors are more prevalent and vary significantly between sexes and racial groups. SEER data also highlights that brain tumors occur at a rate of 7 to 11 cases per 100,000 people annually, with an estimated 227,000 deaths globally each year resulting from this devastating illness. Most cases occur in older age groups, though tumors can affect individuals across all ages, including children and young adults. Cancer, including brain tumors, arises from genetic mutations that disrupt normal cell functions, particularly growth and division. Tumors are categorized into two types:

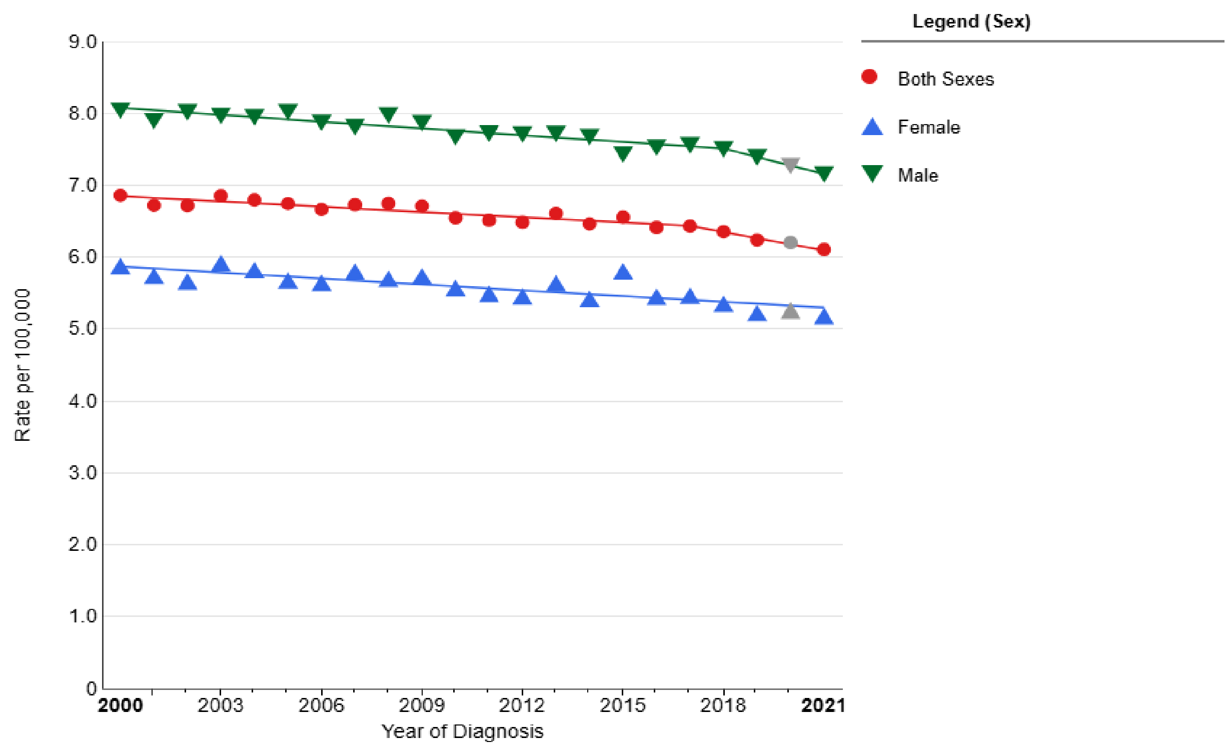

Fig. **Error! No text of specified style in document.**.2.2Deaths per 100,000 population, males, and females by cancer.

Benign tumors: Slow-growing cells that typically do not spread to other tissues. Malignant tumors: Aggressive and fast-growing cells that invade surrounding tissues. While the risk of cancer increases with age about 87% of all cancers in the U.S. are diagnosed in people aged 50 or older—other factors, such as genetics, lifestyle, and environmental exposures, play a crucial role in determining cancer risk.

What is a Brain Tumor?

A brain tumor is a mass or growth of abnormal cells In the brain. Brain tumors can be classified into two types: benign (non-cancerous) and malignant (cancerous). The exact cause of brain tumors is often unknown, but several factors, such as genetics, environmental exposure, or a combination of both, can contribute to their development. Brain tumors can occur at any age, although certain types are more comm- on in specific age groups.

Brain cancer is relatively rare compared to other cancers, but it can be deadly if not detected early. It is considered one of the most serious forms of cancer due to the critical nature of the brain's functions. Brain tumors can develop in various parts of the brain, affecting motor skills, speech, vision, and even personality**.**

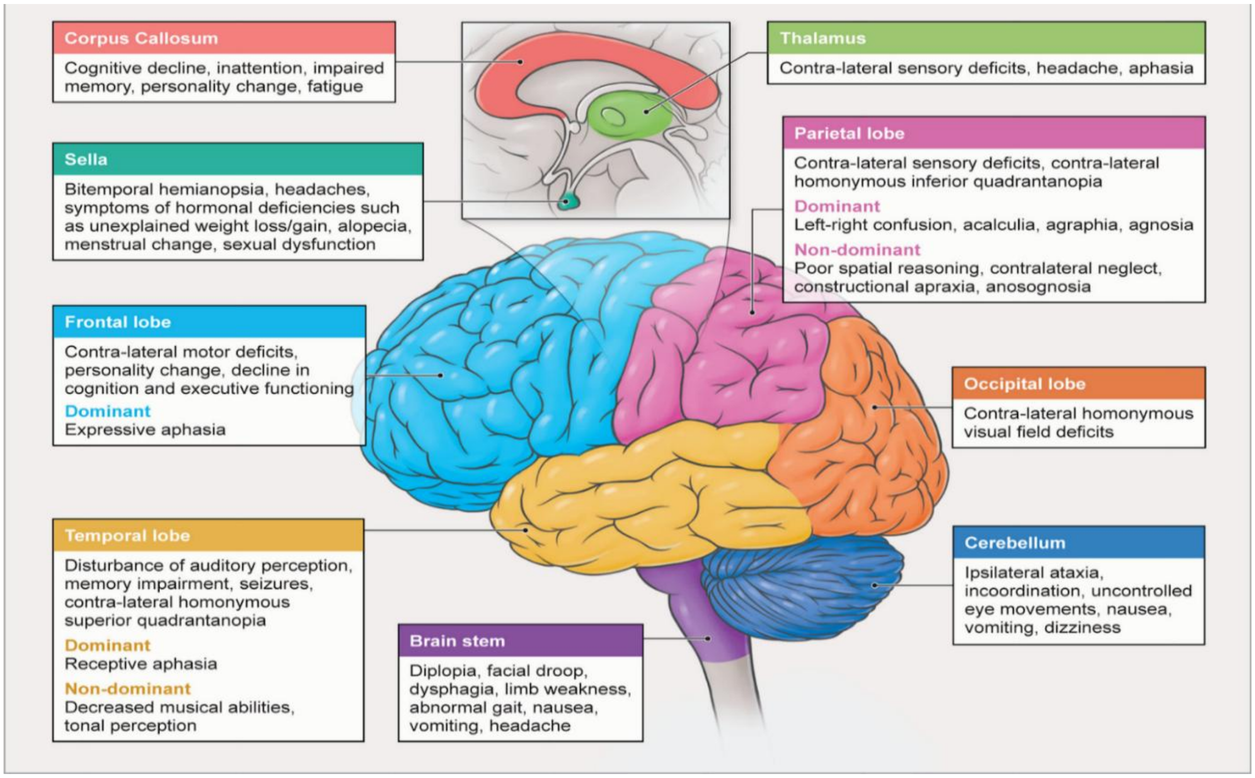

Fig. 3.**Error! No text of specified style in document.**.3Focal symptoms of malignant CNS tumors.

The prognosis for patient with brain tumors depends on factors such as the tumor's size, location, and type (benign or malignant). Some brain tumors can be surgically removed or treated with radiation therapy or chemotherapy, while others may be difficult to treat due to their location or aggressiveness.

Signs and symptoms of a brain tumor can vary depending on its size, location, and growth rate, but common symptoms include:

1. Frequent headaches that may worsen over time or become more intense in the morning.
2. Seizures or convulsions.

3. Nausea or vomiting, particularly in the morning.
4. Vision problems, such as double vision or blurry vision.
5. Personality or memory changes.
6. Weakness or numbness in parts of the body.
7. Speech or coordination problems.
8. Dizziness or balance issues.

Brain tumors often start from non-cancerous growths (benign tumors) that may grow over time. Some benign tumors can turn malignant if left untreated, especially in certain areas of the brain where they might interfere with normal brain functions.

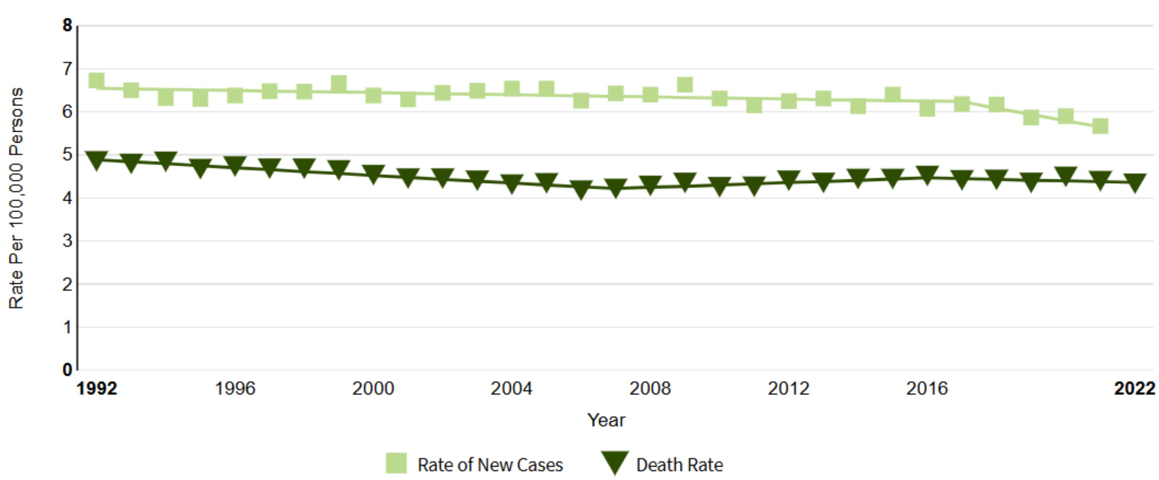

Fig. **Error! No text of specified style in document.**.44Rate of new cases and death rate per 100,000 persons.

Brain tumors are typically diagnosed through imaging tests like MRI or CT scans, which help visualize the location and size of the tumor. In some cases, a biopsy may be required to determine the exact type of tumor. A biopsy involves removing a small sample of the tumor tissue for laboratory analysis.

Treatment for brain tumors may include surgery, radiation therapy, or chemotherapy, depending on the tumor's type, location, and size. Surgery is often the first treatment option if the tumor is accessible and can be safely removed. However, some brain tumors are inopera- ble due to their location, and radiation or chemotherapy may be used to shrink or manage the tumor.

Detection

Medical image detection is a type of artificial intelligence (AI) that involves using machine learning algorithms to automatically detect specific features or abnormalities in medical images. These medical images can include X-rays, CT scans, MRI scans, ultrasound images, and others.

The goal of medical image detection is to assist healthcare professionals in identifying and diagnosing various medical conditions. For example, a machine learning algorithm can be trained to detect brain tumors in MRI scans.

To develop a medical image detection model, a large number of Brain Tumor MRI Dataset images are typically used to train the algorithm. The algorithm learns to identify patterns and features in the images that are associated with different types of brain tumors or normal brain tissue. Once the model is trained,it can be used to automatically detect brain tumors in new, unlabeled MRI scans.

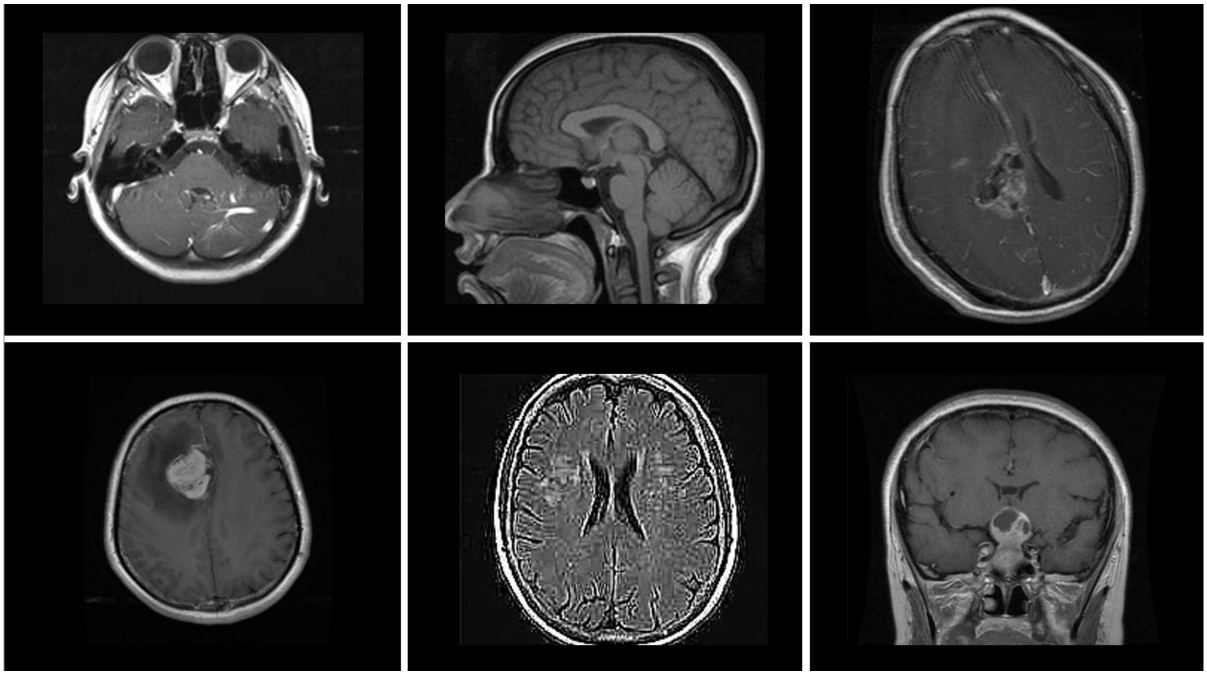

Fig. **Error! No text of specified style in document.**.55Brain Tumor MRI Dataset example

Medical image detection has the potential to improve the efficiency and accuracy of diagnosing conditions like brain tumors, reduce the workload of radiologists, and ultimately improve patient outcomes. It is an active area of research and development in the field of medical imaging and artificial intelligence.

Segmentation

Medical image segmentation is a technique in image processing that involves partitioning medical images into multiple regions or segment based on their content. The goal of medical image segmentation is to identify specific structures or regions of interest within the image, such as organs, tumors, blood vessels, or bones. Once these regions are identified, they can be analyzed and measured to provide valuable diagnostic insights for healthcare professionals.

Medical image segmentation is typically performed using computer algorithms that are trained to recognize patterns and features in medical images corresponding to different structures or regions. Several methods are employed for segmentation, including thresholding, region growing, edge detection, and machine learning-based approaches.

In clinical practice, medical image segmentation has various applications, such as treatment planning, disease diagnosis, and monitoring the progression of medical conditions. One common use is in the segmentation of tumors for more accurate diagnosis and treatment planning.

The current study focuses on semantic segmentation of brain regions to enable the automatic detection of brain tumors using machine learning-based techniques. The deep residual convolutional neural network (CNN) is used to accurately segment brain tumors of varying sizes within the complex brain anatomy. This segmentation technique has significantly improved the accuracy of brain tumor diagnosis by overcoming challenges like the presence of overlapping structures and inconsistent tissue boundaries.

In this segmentation approach, the algorithm is trained using the Figshare dataset, which contains labeled MRI images of brain tumors These images are manually segmented by medical experts, and the corresponding labels are provided to the algorithm. The algorithm learns to identify patterns and features in the labeled images, which it then uses to segment new, unlabeled images. The limitations of manual analysis and the potential of these automated techniques form the primary motivation for our project, TumorXtract.

Overall, medical image segmentation plays a critical role in healthcare by enabling more precise and automated diagnosis of brain tumors. It is a rapidly evolving field in medical imaging, with ongoing advancements in deep learning driving the development of more effective and efficient segmentation models.

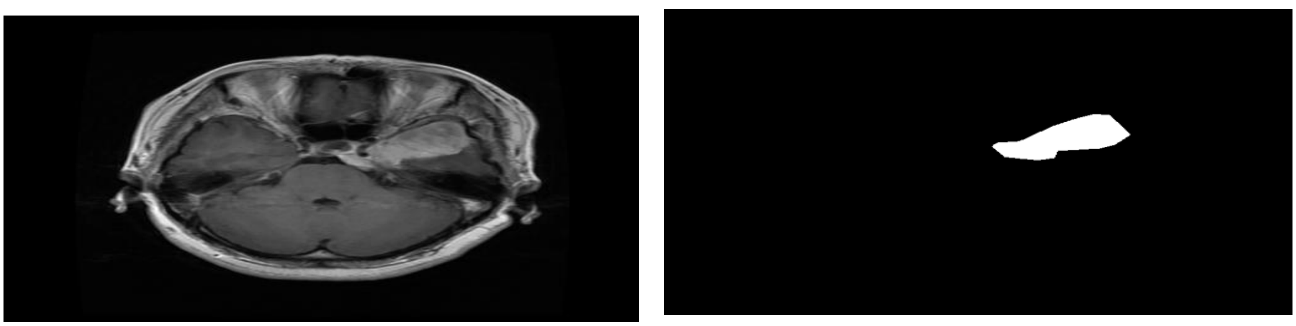

Fig. **Error! No text of specified style in document.**.6Brain Tumor MRI segmentation example.

1.1 Motivation

1. **Improved Patient Outcomes:** Detection of brain tumors significantly improves patient outcomes by allowing for earlier treatment, which can result in a better prognosis and increased chances of survival.
2. **Reduced Healthcare Costs:** Late-stage brain tumors are often more difficult and expensive to treat than early-stage tumors, as they may require more aggressive treatment options and longer hospital stays.

Detecting a brain tumor earlier can help reduce healthcare costs by enabling earlier and less invasive treatment.

3. **Streamlining Clinical Workflow:** The manual review of MRI scans and the subsequent creation of reports is a time consuming process for clinicians. Our system addresses this by automating the initial detection and segmentation tasks and providing a feature to instantly generate standardized PDF reports of the analysis, significantly reducing manual documentation effort and improving workflow efficiency.

4. **Centralizing Patient and Analysis Data:** Healthcare professionals often face the challenge of managing patient information and their corresponding imaging results in separate systems. This project was motivated by the need for an integrated platform where patient records are directly linke to their AI-driven analysis. This creates a single, holistic view for each case, simplifying patient manag-ement and follow-up.

1.2 Problem Definition

The problem this project addressed was the need for an early detection system for brain tumors using detection & segmentation techniques. Brain tumors can often be difficult to detect in their early stages, and timely diagnosis is crucial for improving patient outcomes . Early detection and intervention can significantly enhance survival rates, as treatment is more effective when the tumor is localized and hasn't spread. The challenge is that many brain tumors present with non-specific symptoms, making early identification difficult without advanced imaging techniques.

Currently, medical imaging techniques such as MRI scans are the gold standard for detecting brain tumors. However, the process of manually analyzing these scans is labor-intensive, and there is a risk of human error. Radiologists often face the challenge of distinguishing between tumors and normal brain tissue, especially in complex cases where tumors are small or located in difficult-to-visualize regions of the brain. This can lead to delayed diagnoses, suboptimal treatment planning, and poorer patient outcomes.

The specific problem we aimed to address was the high incidence and mortality rates associated with brain tumors, which are among the most common and dangerous types of tumor worldwide. Traditional manual analysis of brain MRI scans is not always accurate, and tumors may be missed, especially in the early stages. This leads to delays in diagnosis and treatment, resulting in lower survival rates and higher healthcare costs.

Our project addressed this problem by developing a machine learning-based system that can automatically analyze brain MRI scans, accurately detecting and segmenting brain tumors. This system leverages detection and segmentation techniques, specifically semantic segmentation, to identify and analyze suspicious regions of the brain. By automating this process, the system enables earlier and more accurate detection of brain tumors, improving treatment outcomes and potentially saving lives. The system assists doctors by providing precise information about the tumor's location and characteristics, allowing them to make informed decisions about the best treatment options.

1.3 Accomplished objective

The primary goal of this project is to develop a robust and accurate system capable of classifying brain MRI images into categories (non-tumor, pituitary tumor, glioma, or meningioma) and segmenting abnormal regions in the brain indicative of a tumor. The system was designed to assist healthcare professionals in making timely and accurate diagnoses, ultimately improving patient outcomes.

Specifically, the objectives of our project include:

1. **Developed and Trained Advanced Detection Models:** We successfully developed and trained multiple state-of-the-art Convolutional Neural Networks (CNNs), including Xception , EfficientNet, and ResNet, to accurately classify brain MRI images into their respective categories.
2. **Implemented a State-of-the-Art Segmentation Model:** An attention U-Net model was successfully implemented to precisely segment tumor regions from surrounding healthy tissue, which is a critical step for accurate diagnosis and treatment planning.
3. **Performed Rigorous Performance Evaluation:** The performance of all developed models was thoroughly evaluated using standard metrics such as accuracy, precision, and recall, which validated their effectiveness and reliability against a dedicated test set.
4. **Delivered a Full-Featured Clinical Platform:** The AI models were integrated into a secure, web-based platform. This system was built with an ASP.NET Core backend and a Vanilla JS frontend and includes includes critical features such as robust user authentication, patient record management, role-based access for doctors and assistants, and automated PDF report generation.

5. **Validated the System on a Large-Scale Dataset:** The entire system was trained and validated on a large, diverse dataset combining images from Figshare, SARTAJ, and Br35H, ensuring the models' generalization capabilities.

Overall objective: The ultimate aim of this project is to develop a reliable, accurate, and accessible system for the detection and segmentation of brain tumors. By enabling early and precise identification of brain abnormalities, the system will enhance patient outcomes, reduce the burden on healthcare professionals, and provide a valuable tool for screening, diagnosis, and treatment planning.

1.4 Development Methodology and Technology Stack

Our Problem:

Building a machine learning model that can assist doctors in detecting brain tumors and their precise locations using classification and segmentation techniques. This is a critical and challenging task, as accurate and timely detection of brain tumors is crucial for effective treatment. The model will analyze MRI images and accurately classify regions of interest as tumor or non-tumor, while also providing precise segmentation to support treatment planning and monitoring. The success of this project has the potential to save lives by improving the speed and accuracy of brain tumor diagnosis and treatment.

Data Collection:

The figshare dataset and the Brain Tumor MRI Dataset (a combination of figshare, SARTAJ, and Br35H datasets) were used to train our model.

Data Preprocessing:

To optimize the performance of the machine learning model, we employed various preprocessing techniques and data augmentation strategies. These steps were aimed at enhancing the quality and diversity of the training data, minimizing overfitting, and improving the generalization capability of the model.

Model Selection:

For the classification stage of our model, we utilized two state-of-the-art convolutional neural networks (CNNs) - Xception and EfficientNet and ResNet. These models are renowned for their high performance in image classification tasks. Their power enabled the classification stage to accurately differentiate between tumor and non-tumor regions in brain MRI images

For the segmentation stage, we selected the Attention U-Net model. This advanced architecture enhances the standard U-Net by integrating attention gates, which enable the model to automatically learn and focus on target structures of varying shapes and sizes. By concentrating on salient features while suppressing irrelevant regions, the Attention U-Net is designed to provide more precise segmentation of tumor regions. This choice aligns with findings from our literature review, where models utilizing attention mechanisms have demonstrated high accuracy.

Evaluation and Refinement:

The models' performance was quantitatively evaluated against a dedicated test set. Key metrics, including accuracy, precision, and recall, were calculated to validate their effectiveness. The detailed results of this evaluation are presented in Chapter 5.

Deployment:

The system was deployed as a multi-tier application. The client-side, built with Vanilla JavaScript, communicates with a secure ASP.NET Core backend that manages business logic, user authentication, and patient data. The backend, in turn, orchestrates analysis requests to a separate AI service built with Flask, which hosts the trained deep learning models.

Technology Stack

The following tools, frameworks, and libraries were used to build the TumorXtract system:

- **AI & Data Science:** Python, TensorFlow, Keras, Scikit-learn, OpenCV, NumPy, Pillow
- **Backend:** ASP.NET Core, Entity Framewok, C#, REST API, SQL Server

- **Frontend:** HTML, CSS, JavaScript
- **Development & Collaboration:** Visual Studio, Visual Studio Code, Google Colab, Kaggle, Figma

Chapter 2

Literature Review / Related Work

Detection papers

- **MRI brain tumor detection using deep learning and machine learning approaches[6]**
  - **Year:** 2/01/2024
  - **Their solution:** The study proposes a novel approach to brain tumor detection and classification using a combination of deep learning (DL) and machine learning (ML) techniques. The solution integrates preprocessing (ACEA & Median filter), segmentation (FCM), feature extraction (GLCM), and classification methods to improve accuracy and efficiency in identifying brain tumors.
  - **Dataset:** Not provided but their used 255 image MRI T1
  - **Their results:**

Table **Error! No text of specified style in document.**.1Results of paper 1

Model	Accuracy
EDN-SVM	97.93 %

  - **Work Limitation**
    - **Software Integration:** The algorithms developed need to be integrated into clinical software systems for practical use by healthcare professionals.
    - **Grayscale Image Limitation:** The proposed methodology currently works only with grayscale images. Future studies can extend this approach to color images to explore additional features and improve accuracy.
    - **3D Brain Scans:** he method should be adapted for 3D brain scans, enabling more precise brain tumor segmentation and analysis.

- **Optimized CNN Using Manta-Ray Foraging Optimization for Brain Tumor Detection.[7]**
  - **Year:** 20/04/2024
  - **Their solution:** Manta Ray Foraging Optimized convolutional Neural Network (MRFO-CNN), CNN-based feature extraction.
  - **Dataset:** Brain Tumor Classification (MRI)
    - **Their results:**

Table **Error! No text of specified style in document.**.2Results of paper

Model	Accuracy
MRFO-CNN	99.3%

- **Work Limitation:**
  - **Binary Classification Limitation:** Expand the model's capabilities by considering multi-modal imaging.
  - **Small Validation Set**: Pursue larger and more diverse datasets to enhance the model's generalizability.
  - **Lack of Clinical Validation:** Collaborate with medical professionals to further validate and improve the model.
  - **Generalization Issues:** Implement continual learning for real-time diagnosis.

- **Brain tumor detection from images and comparison with transfer learning methods and 3-layer CNN.[8]**
    - **Year:** 1/02/2024
    - **Their solution:** The reliance on a multi-layer CNN and CNN-based feature extraction ensures robust hierarchical feature learning enabling the model to effectively capture intricate patterns in brain tumor images for accurate detection and classification.
    - **Dataset:** Brain Tumor Classification (MRI)
        - **Their results:**

Table **Error! No text of specified style in document.**.3Results of paper 3

Model	Accuracy
Multi-layer CNN	91%
VGG16	98%
EfficientNetB4	97%
InceptionV3	96%

- **Work Limitation:**
    - **Lack of Preprocessing:** involving more comprehensive data preprocessing and exploring other deep learning architectures like transformers.
    - **Focus on Classification Only**
    - **Potential Overfitting**
    - **Technical Complexity**
    - **Limited Dataset Quality**

- **Enhancing Medical Diagnostics: Integrating AI for precise Brain Tumor Detection.[9]**
  - **Year:** 1/01/2024
  - **Their solution:** The reliance on neural networks, combined with preprocessing techniques such as resizing, normalization, and transformations, as well as image embedding techniques for feature extraction, ensures efficient handling of image data while enabling the model to learn compact and meaningful representations for accurate brain tumor detection.
  - **Dataset:** Not provided but their 1747 brain MRI images
  - **Their results:**

Table **Error! No text of specified style in document.**.4Results of paper 4

Model	Accuracy
Neural Network	91 %

  - **Work Limitation:**
    - **Computational Resources:** Optimize model architectures to reduce computational demands, enabling deployment in resource-constrained environments.
    - **Dataset Diversity:** Refine AI models with larger and more diverse datasets to enhance accuracy and applicability across demographics.
    - **Interpretability Challenges:** Develop explainable AI techniques to improve model transparency and make diagnostic decisions more interpretable.

- **A Supervised ML Applied Classification Model for Brain Tumors MRI.[10]**
  - **Year:** 8/04/2024
  - **Their solution:** The reliance on algorithms such as Decision Tree, Support Vector Machine, K-Nearest Neighbors, and Neural Network, along with 30 extracted features from MRI images (both categorical & numerical), ensures a multi-algorithmic approach for classification, leveraging diverse feature type to enhance predictive accuracy.
  - **Dataset:** the REMBRANDT dataset from The Cancer Imaging Archive (TCIA).
  - **Their results:**

Table **Error! No text of specified style in document.**.5Results of paper 5

Model	Accuracy
DT	96.2%
SVM	94.9%
KNN	93.7%
NN	92.4%

  - **Work Limitation:**
    - **Lack of Exploration of Advanced Techniques:** Incorporate more advanced ML nd DL techniques to improve model performance and generalizability.
    - **Focus on Classification Only**: Expand research to include segmentation and localization tasks for a more comprehensive understanding of brain tumors.
    - **Potential Overfitting:** Collect a larger and more diverse dataset to improve the model's robustness and reduce the risk of overfitting.

- **Classification of brain tumor types through MRIs using parallel CNNs and frefy optimization.[11]**
  - **Year:** 1/07/2024
  - **Their solution:** The reliance on PCNN, supported by preprocessing techniques like background removal, normalization, and histogram equalization, along with feature extraction using Local Binary Patterns (LBP) and 2 CNN features, ensures effective feature representation while maintaining robust preprocessing for enhanced accuracy in image-based analysis.
  - **Dataset:** Not mentioned
  - **Their results:**

Table **Error! No text of specified style in document.**.6Results of paper 6

Model	Accuracy
PCNN	98.6%

  - **Work Limitation:**
    - **Insensitivity to Detail Features in Classic FPN:** Enhance the model by integrating more advanced feature extraction techniques to capture finer image details.
    - **Complexity of Model:** Simplify the model architecture or optimize computational performance to ensure scalability and usability.
    - **Potential for Overfitting:** Increase dataset size and diversity, and incorporate regularization techniques to mitigate overfitting risks.
    - **Clinical Validation:** Collaborate with medical professionals to validate the model in clinical settings and gather expert feedback.

Segmentation Papers

- **High-Resolution Model for Segmenting and Predicting Brain Tumor Based on Deep UNet with Multi Attention Mechanism.[12]**
  - **Year:** 17/01/2024
  - **Their solution:** The reliance on UNet with a multi-attention mechanism, combined with pixel-based segmentation and feature extraction using Local Binary Patterns(LBP) and 2D CNN features, enables precise segmentation by effectively capturing spatial and texture-based details from image data.
  - **Dataset:** BraTS 2020 Dataset
  - **Their results:**

Table **Error! No text of specified style in document.**.7Results of paper 1

Model	Accuracy
UNet with Multi-Attention Mechanism	99%

  - **Work Limitation:**
    - **Model Complexity:** Optimize the attention mechanisms and streamline the architecture to reduce computational overhead while maintaining performance.
    - **Limited to 2D:** Explore advanced deep learning architectures capable of handling 3D data for more precise and comprehensive segmentation.

- **Brain Tumor Segmentation and Classification using Optimized Deep Learning.[13]**
  - **Year:** 1/06/2024
  - **Their solution:** The system utilizes Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, which are well-suited for handling the spatial and temporal aspects of imaging data. Preprocessing techniques, including Gaussian filtering for denoising, image sharpening, and skull stripping, enhance the clarity and usability of MRI scans. For feature extraction, the Gray-Level Co-occurrence Matrix (GLCM) is employed, which is effective in capturing textural information crucial for medical image analysis. A pixel-based segmentation approach ensures a detailed and granular analysis of the MRI data, enabling precise localization of relevant features
  - **Dataset:** Not provided
  - **Their results:**

Table **Error! No text of specified style in document.**.8Results of paper 2

Model	Accuracy
CNN	84.5%
LSTM	83.71%

  - **Work Limitation:**
    - **Complexity of Medical Imaging:** Medical imaging often involves complex anatomical structures and variations, making it challenging to develop a universally effective model.
    - **Complexity of Medical Imaging:** Medical imaging often involves complex anatomical structures and variations, making it challenging to develop a universally effective model.

Work Differences

1. We applied detection and segmentation techniques together to help detect brain tumors.

2. We implemented multiple augmentation techniques.

3. Unlike other studies that used datasets with low-quality images, our dataset consisted of high-quality, clean, and ready-to-train images, eliminating the need for additional preprocessing steps.

4. we applied advanced techniques to prevent overfitting, ensuring the model generalized well across new data.

5. Our dataset is significantly larger and more comprehensive than those used in other studies, which often relied on small datasets with limited variability

6. We carefully considered the sizes and variability of tumors and other structures within the brain to improve detection and segmentation accuracy.

7. We reduced the complexity models while improving results, achieving a final accuracy of 98.78% with our EfficientNet model, a result that is highly competitive with the reviewed works.

8. We achieved these results using the available computational resources, which are lower than the resources used in many comparable works.

9. We developed a user-friendly GUI for healthcare professionals, allowing them to use our model not only to detect brain tumors but also to provide detailed segmentation for better decision-making and treatment planning.

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Chapter 3

Proposed system

3.1 Overview

The proposed system, **TumorXtract**, is a comprehensive, web-based clinical support platform designed to assist medical professionals in the early and accurate diagnosis of brain tumors. The system leverages state-of-the-art deep learning models to automate the analysis of Magnetic Resonance Imaging (MRI) scans, addressing the challenges of manual interpretation, which can be time-consuming, labor-intensive, and prone to human error.

The primary goal of TumorXtract is to provide a seamless, integrated workflow for clinicians—from patient management to advanced AI-driven image analysis and report generation. By combining a robust backend, an intuitive user interface, and a powerful, decoupled AI service, the system aims to enhance diagnostic accuracy, streamline clinical workflows, and ultimately improve patient outcomes through timely intervention. The target users are medical professionals, including radiologists, oncologists, and their authorized assistants.

3.2 Approach used to solve the problem

The fundamental problem addressed is the need for an early, accurate, and efficient system for brain tumor detection and segmentation. Traditional manual analysis of MRI scans by radiologists is labor-intensive, time-consuming, and prone to human error, which can lead to delayed diagnoses and poorer patient outcomes.

Our proposed solution, Tumor Xtract, tackles this challenge through a comprehensive, multi-stage approach that integrates advanced machine learning with a secure clinical web platform. The core of our approach is a two-step AI pipeline designed for maximum accuracy and utility:

1. **Detection and Classification:** An initial AI model first analyzes an uploaded MRI scan to determine if a tumor is present. If a tumor is detected, the model classifies it into one of the known types (Glioma, Meningioma, or Pituitary tumor). This initial screening step is crucial for quickly flagging suspicious cases.

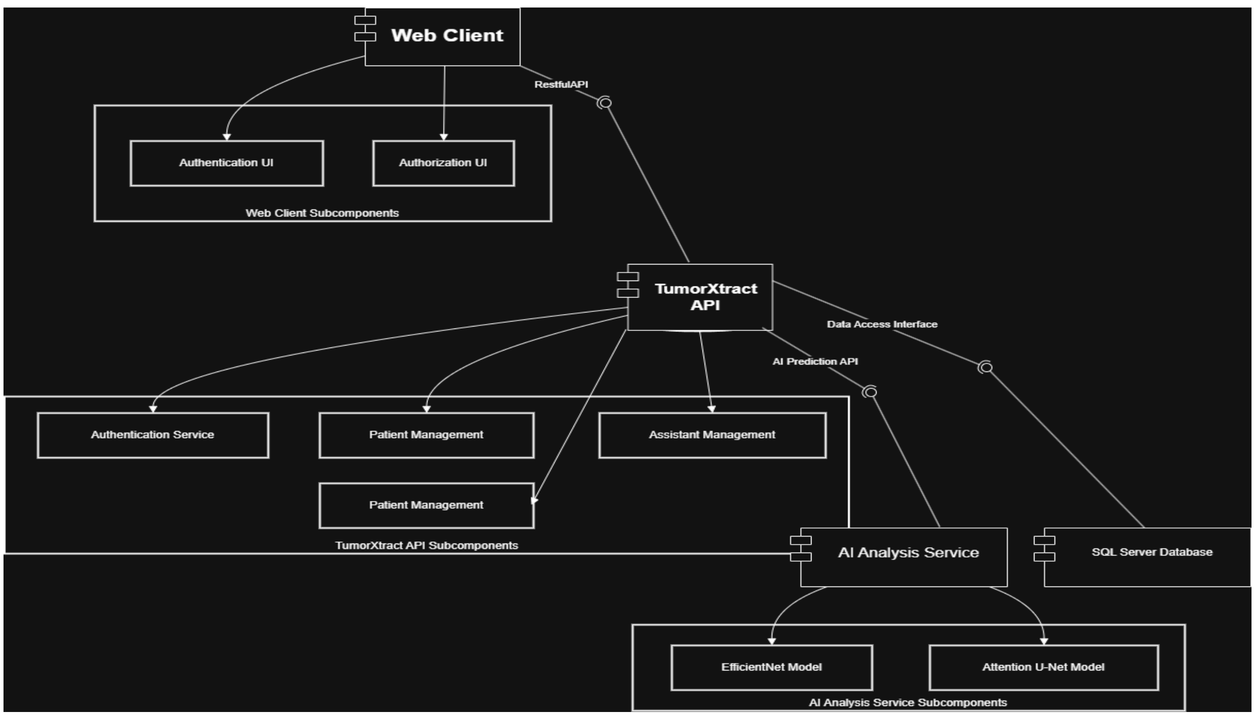
2. **Segmentation:** If a tumor is detected, the MRI scan is automatically passed to a second, specialized AI model. This model performs semantic segmentation, precisely outlining the tumor's boundaries pixel-by-pixel. This generates a segmentation mask that is critical for assessing the tumor's size and location, which informs surgical planning and treatment monitoring.

This AI pipeline is encapsulated within a distinct microservice, which is then integrated into a full-featured, secure web application. This platform allows clinicians (Doctors and their Assistants) to manage patient records, upload MRI scans for analysis, view the AI-generated results, and generate comprehensive PDF reports. This holistic approach not only automates the diagnostic process but also streamlines the entire clinical workflow from patient data entry to final report generation.

3.3 System architecture

The Tumor Xtract system is designed using a modern, multi-tier Layered Client-Server architecture to ensure separation of concerns, scalability, and maintainability. The architecture consists of three primary, decoupled components: a Frontend Web Client, a Backend API, and an externalized AI Service.

Fig. **Error! No text of specified style in document.**.7System component diagram



The architecture is composed of the following layers:

- **Client-Server Model:** The system clearly separates the presentation layer (the web interface used by doctors) from the backend processing and data layers.

- **Layered Backend Architecture (ASP.NET Core):** The backend is built with a layered design for maintainability and separation of concerns.
  - **API Layer (Presentation):** Contains the controllers responsible for handling HTTP requests from the client, performing input validation (using DTOs), and orchestrating responses.
  - **Service Layer:** Contains the core business logic, coordinating interactions between data repositories and other services like AnalysisService, TokenService, and FileService.
  - **Core Layer (Domain):** Defines the fundamental entities, interfaces for services and repositories, specifications, and other domain-specific logic.
  - **Repository Layer:** Implements the data access logic using Entity Framework Core, managing all communication with the database.
- **Externalized AI Microservice (Python/Flask):** All machine learning logic is encapsulated in a distinct microservice, decoupled from the main application backend. This prevents intensive AI computations from impacting the performance of the user-facing application and allows the AI service to be scaled independently. The service exposes a secure HTTP endpoint (`api/predict`) that accepts the MRI scan and returns a structured JSON response with the analysis results.
- **Database:** A relational **Microsoft SQL Server** database is used to store all persistent data

3.4 Algorithms and Frameworks Used

The proposed system is built upon a foundation of state-of-the-art machine learning models and robust software development frameworks.

- **Core Algorithms:**

  The diagnostic power of the TumorXtract system is driven by a sophisticated two-stage AI pipeline, which is composed of state-of-the-art deep learning models. This chapter provides a detailed examination of the core algorithms selected for both the detection and segmentation tasks. For each model, we discuss its architecture, the rationale for its selection, and the specific training configurations used to optimize its performance. The models were implemented using the Python ecosystem, primarily leveraging the TensorFlow and Keras libraries for deep learning, and served via a Flask microservice.

  1. The analysis workflow operates in two sequential steps:
     - **Detection and Classification:** An MRI scan is first analyzed to determine if a tumor is present and, if so, to classify its type.
     - **Segmentation:** If a tumor is detected, a second model is employed to precisely outline the tumor's boundaries.

To ensure the highest level of accuracy for tumor detection, three powerful Convolutional Neural Network (CNN) architectures were developed and evaluated: EfficientNet-B3, ResNet50, and Xception. While all models performed well, EfficientNet-B3 was selected as the primary model for the final system due to its superior balance of high precision and a low false-negative rate, which is critically important in a clinical setting to avoid missing actual tumors.

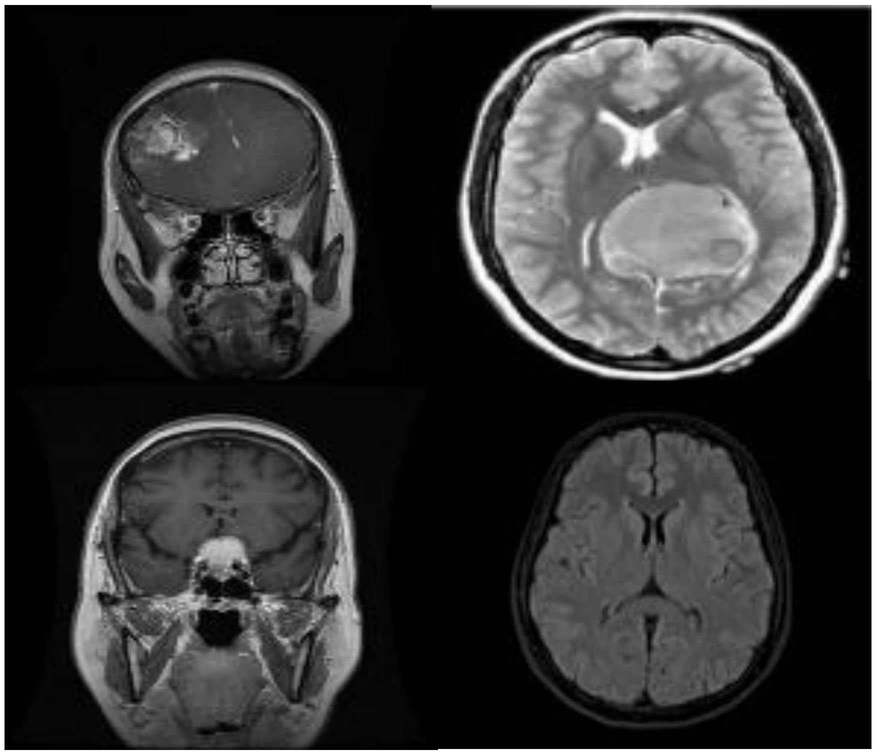
1. Data Collection

- We are using two datasets: the Brain Tumor Segmentation dataset and the Brain Tumor Detection MRI dataset.
- For the detection part: we are using the Brain Tumor Detection MRI dataset.
  This dataset is categorized into four types: meningioma, glioma, pituitary tumor, and no tumor.
- This dataset is a combination of the following three datasets
  Figshare
  SARTAJ dataset
  Br35H
- For the segmentation data, we are using the Brain Tumor Segmentation dataset. This dataset consists of three types of brain tumors: glioma, meningioma, and pituitary tumor.
- The dataset is obtained from Figshare and includes masks for each type of tumor.
- The detection dataset consists of 7,022 images and is divided into four classes: glioma, meningioma, pituitary tumor, and no tumor. The dataset was originally divided into training and testing parts.

Table **Error! No text of specified style in document.**.9Number of the images for each class in dataset

Glioma	Meningioma	Pituitary	No Tumor
1621	1645	1757	2000

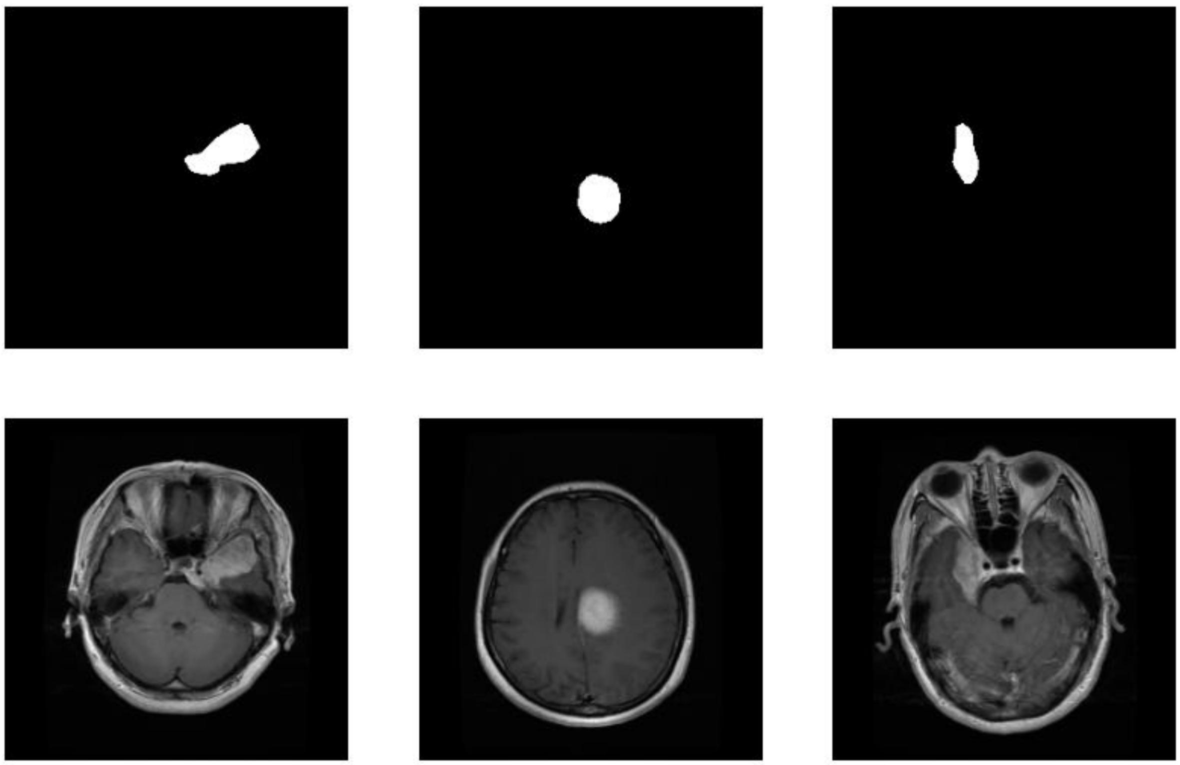
- The data is collected from multiple sources, including Figshare the SARTAJ dataset, and Br35H. It is clean and well-organized, and it has been used in several research projects with promising results.



- **For the segmentation part:** The dataset is obtained from Figshare. It is clean, well-prepared, and was last updated on December 21, 2024, making it one of the most recent datasets available. Since we need data that covers different tumor types to perform accurate segmentation, this dataset was the most suitable choice.
- Although the dataset includes images of three types of brain tumors - meningioma (708 images), glioma (1,426 images), and pituitary tumor (930 images) the images are not labeled by class and are provided as general tumor images without specific categorization.

- The dataset consists of a total of 6,128 images, split equally into 3,064 images and 3,064 corresponding masks.

Fig. 5.37Example segmentation Dataset



2. Preprocessing

- **Part 1: Detection**

  While the detection dataset was already clean and balanced, data augmentation was applied to enhance the model's ability to generalize and to reduce the risk of overfitting. These techniques create variations of the

  training images, allowing the model to learn more robust features. The applied augmentation techniques included:

  - Rescaling

  - Brightness range adjustment: Randomly adjusted brightness within a range of [0.8, 1.2].

- Rotation: Random rotations within a range of ±20 degrees.
- Width and Height shift: Random horizontal and vertical shifts up to 10% of the image dimensions.
- Shear transformation.
- Zoom: Random zooming in by up to 20%.
- Horizontal flip: Applied with a 50% probability.
- Fill mode adjustment.

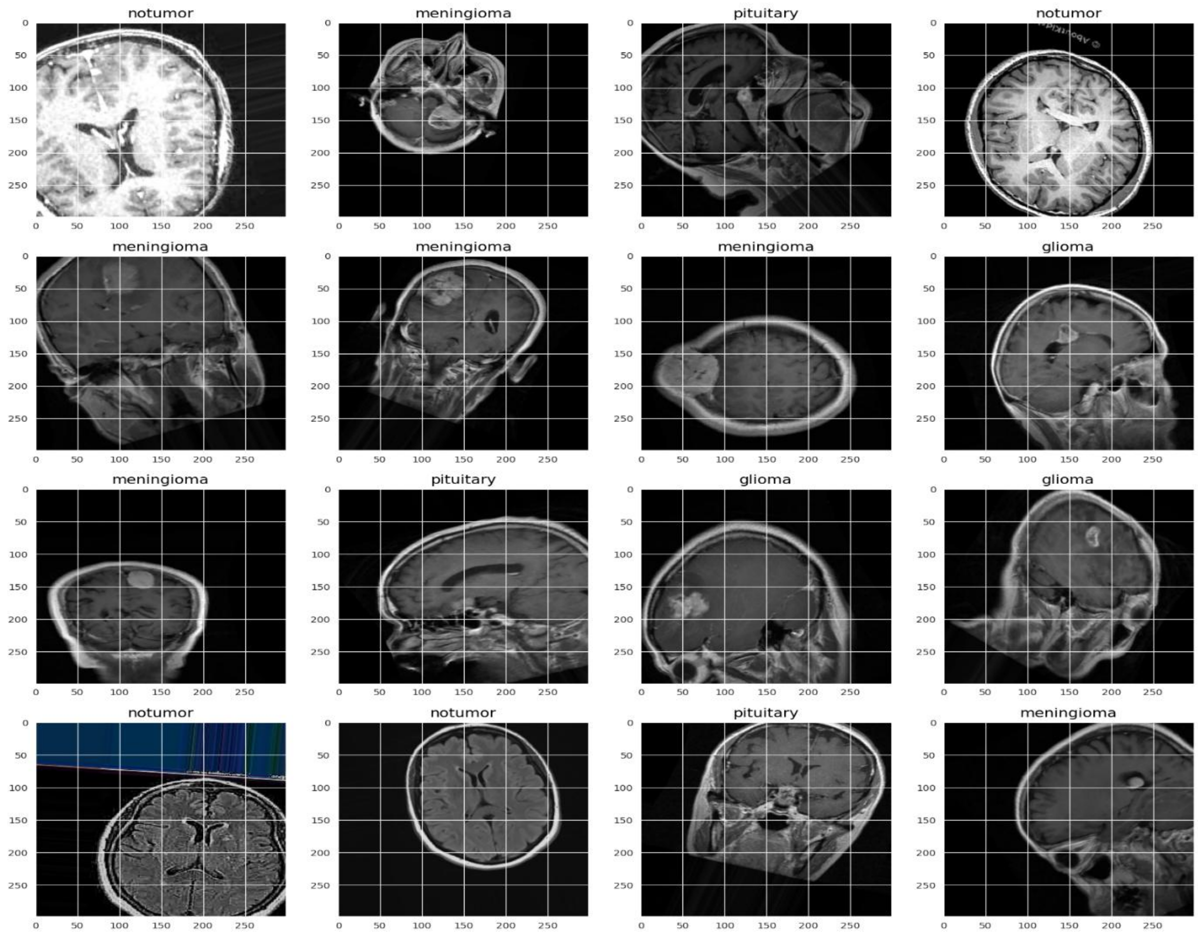


Fig. **Error! No text of specified style in document.**.38some example different augmentations mri for detection

- **Part 2: segmentation**

For the segmentation task, data augmentation was also crucial for preventing overfitting. We carefully selected augmentations that would not destroy the critical features necessary for the segmentation process. These transformations were applied identically to both the images and their corresponding masks. This is essential because the mask is a pixel-wise map of the image, if the image is altered without applying the exact same transformation to the mask, the spatial correspondence is lost, and the model cannot learn correctly.

The applied augmentation techniques included:

- Horizontal Flip
- Rotation
- ShiftScaleRotate
- Elastic Transform

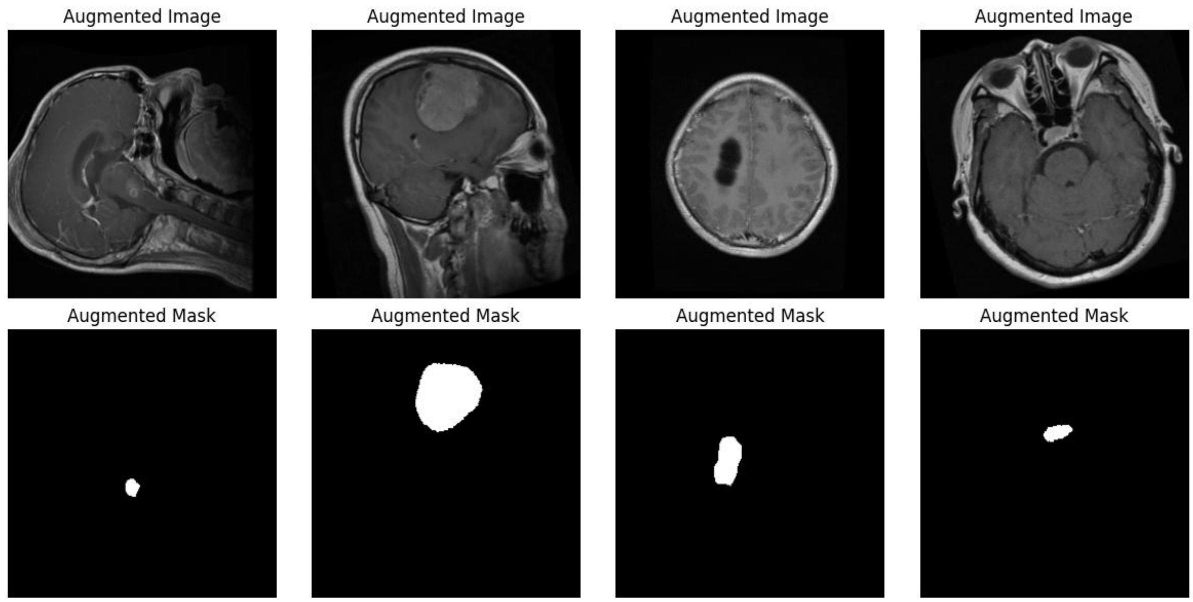


Fig. **Error! No text of specified style in document.**.39some example different augmentations mri for Segmentation

3. Data Splitting

We split the datasets into training, testing, and validation sets. The detection dataset originally consisted of only training and testing parts, so we further split the training part into training and validation sets. As for the segmentation dataset, we divided it into training, testing, and validation sets.

Table **Error! No text of specified style in document.**.10Spliting Dataset

Techniques	Train	Test	Validation
Detection	4855	1311	857
Segmentation	1960	491	613

Fig. **Error! No text of specified style in document.**.45Traing Dataset

Detection

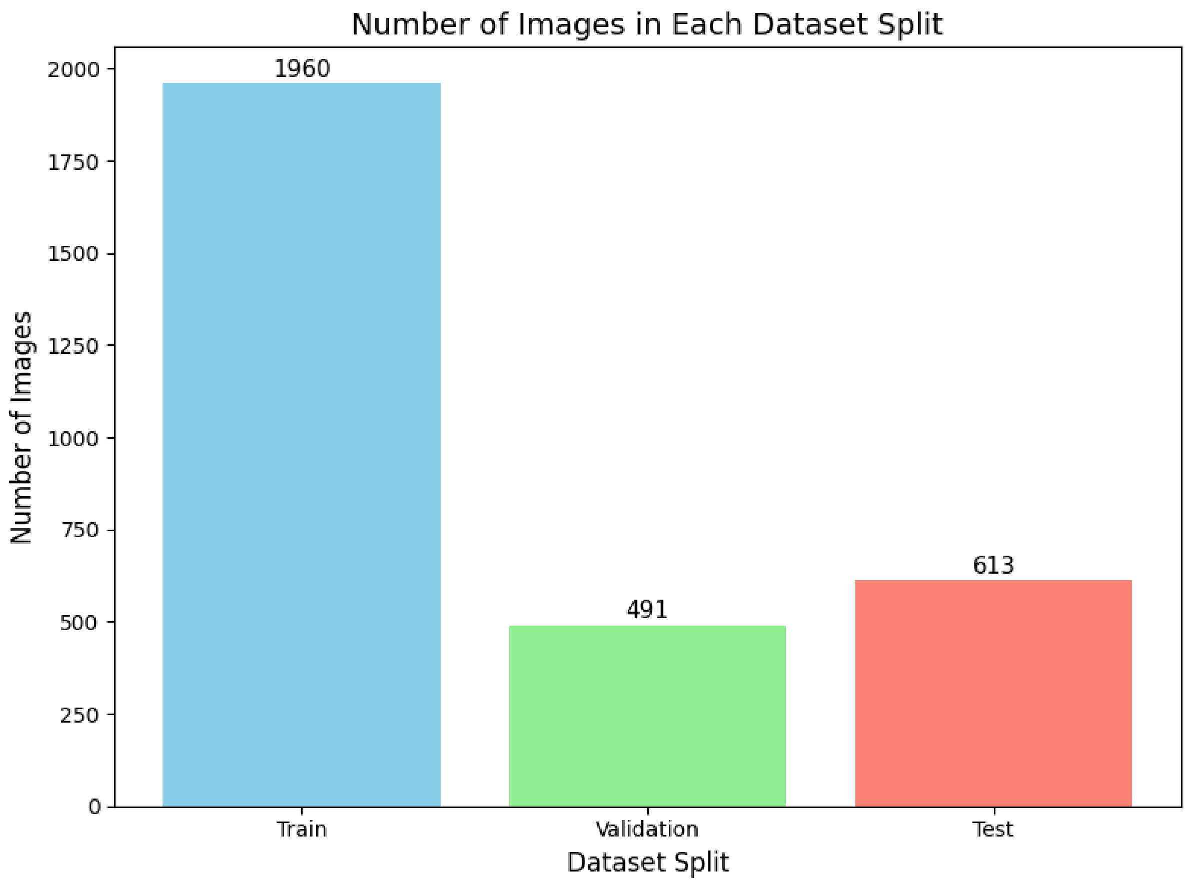


Fig. **Error! No text of specified style in document.**.41Testing Dataset Detection

Fig. **Error! No text of specified style in document.**.42Spliting data segmentation

4. Techniques

- **Detection:**

  Brain tumor MRI images were classified using a Convolutional Neural Network (CNN)-based algorithm, which is effective in automatically learning and identifying tumor patterns from medical imaging data. Initial training on the original dataset without any or preprocessing yielded less-than-ideal results due to overfitting, as the model struggled to generalize well to unseen data.

Since the dataset was clean and of high quality, we applied data augmentation techniques to increase the diversity of the training samples and enhance the model's ability to generalize. We utilized a transfer learning approach, as it is faster to train than a model built from scratch and typically results in better performance on our dataset. However, we did not use the pre-trained models' weights directly but rather trained them from scratch with the addition of some custom final layers. We experimented with three models: Xception, EfficientNet-B3, and ResNet50.

While all three models are powerful deep learning architectures, ResNet50 and Xception showed a significant drawback with higher false negative (FN) rates in our initial experiments. In the context of tumor detection, a high FN rate is particularly dangerous as it means the model is more likely to miss an actual tumor. EfficientNet-B3 addressed this issue effectively by providing a better balance of metrics. Therefore, it was chosen as the primary model for our system due to its combination o high precision and computation efficiency, making it a more reliable choice for detecting brain tumors.

a. EfficientNet-B3 (Primary Model)

EfficientNet-B3 is a convolutional neural network architecture designed to achieve high accuracy while maintaining computational efficiency. Unlike traditional models that simply increase depth or width, EfficientNet-B3 uses a compound scaling method that uniformly scales the network's depth, width, and input resolution, resulting in better performance with fewer parameters. The architecture consists of approximately 55 main layers, including multiple stages of Mobile Inverted Bottleneck Convolution (MBConv) blocks, which capture complex features while keeping computational cost low. The model also ncorporates batch normalization layers to stabilize and accelerate training and typically ends fully connected (Dense) layer to generate the final predictions

I. Custom Layers: We added a batch normalization layer to improve the training speed and stability of the network, along with a final Dense layer with 256 units.

II. Training Process: The model was trained with a batch size of 32 for 10 epochs. We used the Adamax optimizer with a learning rate of 0.001 an categorical cross-entropy a the loss function. a validation set was used throughout the training process to monitor performance and detect overfitting

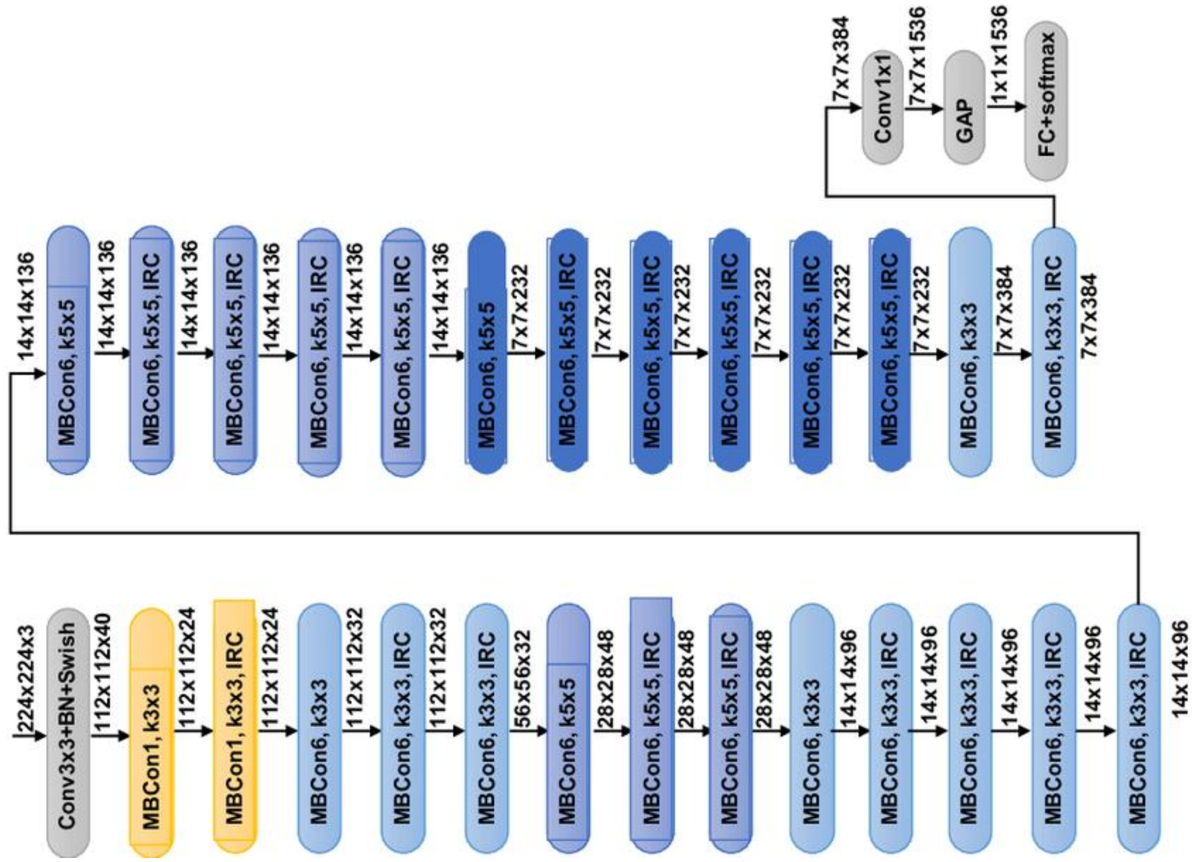


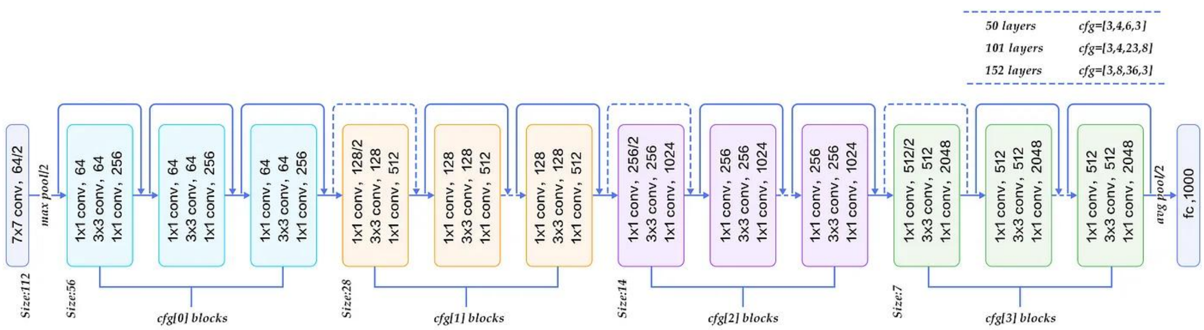
Fig. **Error! No text of specified style in document.**.8r

b. ResNet50 (Benchmark Model)

ResNet50 is a deep neural network architecture introduced by Microsoft Research in 2015. It was designed to address the problem of vanishing gradients in very deep neural networks, which can make training difficult. ResNet50 uses skip connections (or identity mappings) to allow the gradient to flow directly through the network. It has a total of 50 layers, including convolutional, pooling, and fully connected layers, arranged in a series of residual blocks.

I. Custom Layers: We added a batch normalization layer to improve training speed and stability, and a Dense layer with 256 units.

II. Training Process: We conducted two training sessions, one with the pure images and a second with augmented images to address overfitting.



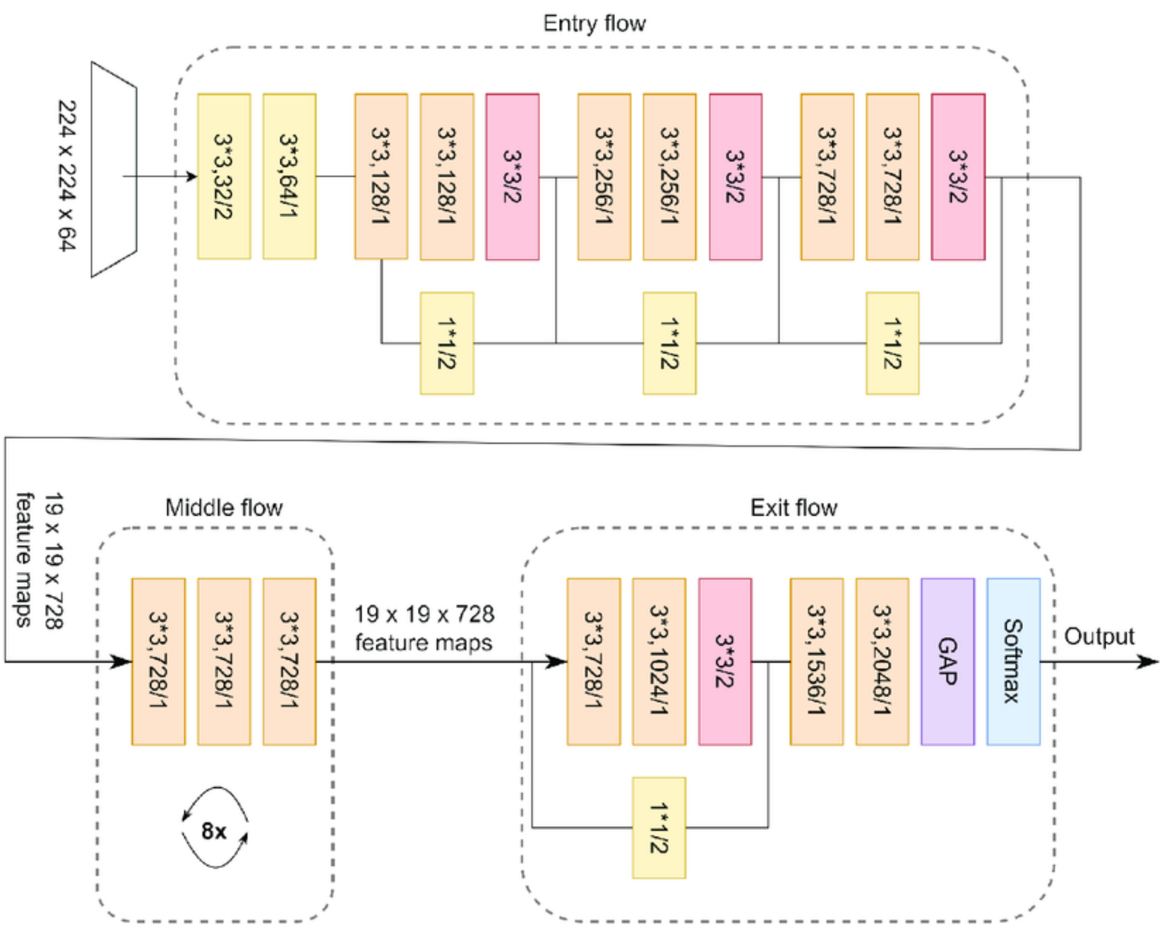
III. Fig. **Error! No text of specified style in document.**.44ResNet50 Architecture

c. Xception (Benchmark Model)

Xception is a CNN architecture developed by François Chollet as an extension of the Inception architecture. It stands for "Extreme Inception" and is specifically designed to improve model efficiency and accuracy by using depthwise separable convolutions instead of standard convolutions. The architecture consists of 71 layers structured into entry, middle, and exit flows, which allows it to extract increasingly abstract features while significantly reducing the number of parameters.

I. Training Process: The model was trained with a batch size of 32 for 10 epochs, using the Adamax

II. optimizer with a learning rate of 0.001 and categorical cross-entropy as the loss function.



Xception Architecture

- **Segmentation**

The brain tumor images were segmented using a deep learning-based semantic segmentation algorithm. This task presented significant challenges due to the complex and irregular shapes of tumors, the presence of noise in MRI scans, and the substantial computational power required for training precise models.

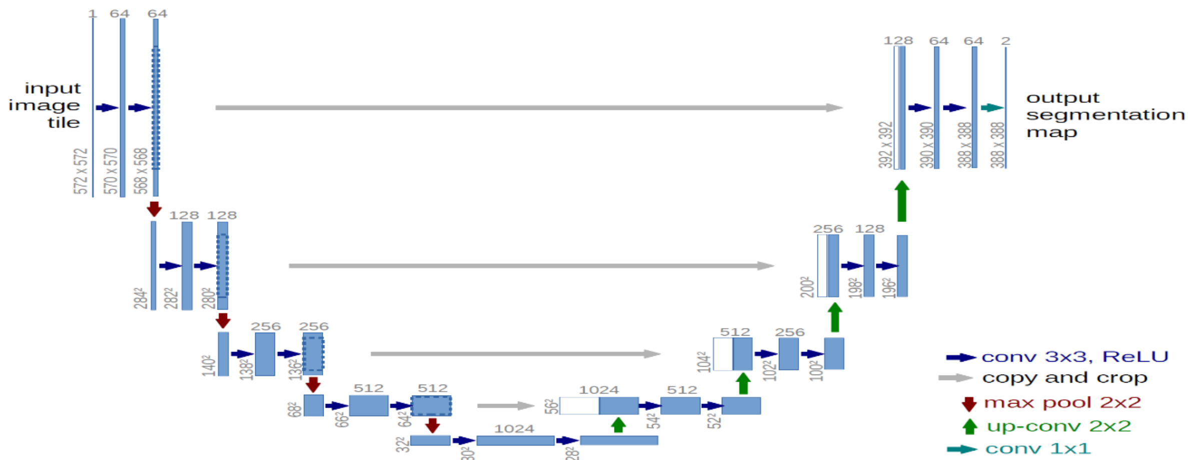
We initially trained the model using the original dataset along with data augmentation to increase the number of training samples. However, this approach resulted in poor performance due to overfitting. To address this issue, we then applied augmentation directly to the existing images without increasing the dataset size, using a careful and controlled manner to preserve the critical features essential for accurate segmentation.

a. U-Net (Primary Model)

For this task, we trained and used the Attention U-Net model. U-Net is specifically designed to leverage the spatial information present in images, which is crucial for achieving accurate segmentation results. Its architecture, which includes symmetric encoder-decoder paths and skip connections, enables the model to capture both low-level and high-level features effectively. The "Attention" mechanism is a further enhancement that allows the model to learn to focus on the most relevant regions of the image for segmentation, which is particularly effective for medical imaging.

I. Training Process: We conducted two primary training sessions. In the second, more successful session, we trained the model on preprocessed images (before augmentation) with a batch size of 10, using Adam as the optimizer with a learning rate of 0.0001 and a Sigmoid activation function, for 30 epochs.

II. Early Stopping: We used an Early Stopping callback with a patience of 5 epochs. This technique monitors the model's performance on the validation set, and if the performance does not improve for a certain number of epochs, the training process is stopped early to prevent overfitting to the training data.



Xception Architecture

- ## Core Frameworks:
  - **Backend:** The server-side application is built with ASP.NET Core, a high-performance, cross-platform framework for building modern web APIs.
  - **AI Service:** The AI microservice is developed using Flask, a lightweight and flexible Python framework ideal for creating model-serving APIs.
  - **Database Management:** Data persistence is handled by **SQL Server**, with **Entity Framework Core** serving as the Object-Relational Mapper (ORM) to manage database interactions.

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Chapter 4

Implementation

This chapter details the practical development and construction of the TumorXtract system, translating the architectural designs and system requirements outlined in previous chapters into a functional, end-to-end application. The implementation process involved three distinct but interconnected development streams: the backend API, the AI microservice, and the frontend web client

4.1 Technologies, Tools, and Programming Languages Used

The development of the TumorXtract system was made possible by a carefully selected stack of modern technologies, frameworks, and libraries. This stack was chosen to ensure robustness, scalability, and maintainability across the different components of the application.

- **AI & Data Science:**
    - Language: Python
    - **Libraries:** TensorFlow, Keras (for building and training deep learning models), Scikit-learn (for machine learning utilities), OpenCV (for image processing), NumPy (for numerical operations), and Pillow (for image manipulation).
- **Backend Development:**
    - **Framework:** ASP.NET Core
    - **Language:** C#
    - **API Style:** RESTful API

- **Database:** Microsoft SQL Server
- **Object-Relational Mapper (ORM):** Entity Framework Core

- **Frontend Development:**
  - **Languages:** HTML, CSS, JavaScript (Vanilla JS)
- **Development & Collaboration Tools:**
  - **IDEs:** Visual Studio, Visual Studio Code
  - **AI Development Platforms:** Google Colab, Kaggle
  - **UI/UX Design:** Figma

4.2 Key Components/Modules of the System

The TumorXtract system is architected as a set of distinct, interacting modules, each with a specific responsibility. This modular design enhances maintainability and allows for independent development and scaling.

- Frontend (Web Client): This is the user-facing component of the system, providing the graphical user interface (UI) for doctors and their assistants. Its key responsibilities include:
  - User authentication (Login/Registration).
  - Patient management (CRUD operations: Create, Read, Update, Delete).
  - Secure upload of MRI scans for analysis.
  - Displaying detection and segmentation results.

  - Profile and assistant management (CRUD operations with permissions).
  - Generation and download of analysis reports in PDF format.

- Backend API (.NET Core Backend): This module serves as the central nervous system of the application. It handles all core business logic, data persistence, and communication between the frontend and the AI service. Its functions include:
  - User Authentication and Authorization: Manages user accounts (Doctors, Assistants) and controls access using JSON Web Tokens (JWT).
  - Patient and Assistant Management: Provides API endpoints for all CRUD operations related to patient and assistant records.
  - AI Analysis Orchestration: Forwards MRI scan requests from the client to the AI service and awaits the JSON response.
  - Data Handling and Persistence: It temporarily stores the immediate results from the AI service. Upon a doctor's confirmation, it permanently links the analysis (including prediction, confidence scores, and image paths) to a patient record in the SQL Server database.
- Externalized AI Microservice (Python/Flask): This module encapsulates all machine learning logic and operates as a distinct microservice. Its workflow is executed in two stages:

1. Stage 1: Detection/Classification: Upon receiving an image, it is first passed to a trained EfficientNet-B3 model to classify the image and determine if a tumor is present.
2. Stage 2: Segmentation: If a tumor is identified, the image is then automatically passed to an Attention U-Net model, which performs semantic segmentation to generate a precise pixel-level mask of the tumor. Finally, the service compiles the results—including the final prediction, confidence scores, and Base64-encoded mask—into a single JSON response that is sent back to the .NET backend.

4.3 Challenges Faced and How They Were Resolved

During the implementation of the TumorXtract system, several technical challenges were encountered. The following section describes these challenges and the solutions that were implemented to overcome them.

- Challenge: Model Overfitting and High False-Negative Rates
    - Problem: Initial training of the detection models on the original dataset led to overfitting, where the model performed well on training data but struggled to generalize to new, unseen images. Furthermore, initial benchmark models like ResNet50 and Xception exhibited higher false-negative (FN) rates, which is critically dangerous in a medical context as it means missing an actual tumor.

   - Solution: This was addressed through a multi-faceted approach. First, we implemented a robust data augmentation pipeline (including rotations, shifts, and brightness adjustments) to artificially increase the diversity of the training data. Second, we selected EfficientNet-B3 as our primary model because it provided a superior balance of high precision and recall, significantly reducing the false-negative rate. Finally, we used the Early Stopping technique during training to prevent the model from overfitting by monitoring validation performance.

- Challenge: System Performance and Scalability

   - Problem: The deep learning models for detection and segmentation are computationally intensive. Integrating them directly into the main backend could lead to slow response times and a poor user experience, especially under concurrent user load.

   - Solution: We resolved this by adopting a microservice architecture. The AI models were deployed in a separate, externalized Flask service. This decouples the intensive AI processing from the primary user-facing application, ensuring the main API remains responsive. This design also allows the AI service to be scaled independently as demand grows.

- Challenge: Data Quality and Preprocessing

- Problem: Medical imaging datasets can often be inconsistent or contain noise. The segmentation masks, in particular, required careful handling to be suitable for training.
- Solution: We addressed this by selecting high-quality, clean, and well-organized datasets (Figshare, SARTAJ, and Br35H). For the segmentation task, specific preprocessing steps were applied to the masks, including thresholding to convert them into a binary format and smoothing techniques to remove noise and artifacts. This ensured the models were trained on reliable, high-fidelity data.

Chapter 5

Testing & Evaluation

The validation of the TumorXtract system was a critical phase designed to ensure its functional correctness, measure its performance against rigorous metrics, and contextualize its contributions within the existing landscape of brain tumor analysis tools. This chapter details the comprehensive testing and evaluation methodologies applied at every level of the system, from the individual AI models and backend API endpoints to the end-to-end user workflow.

The evaluation process was multifaceted, encompassing three key areas:

1. **Testing Strategies:** Verifying the reliability and correctness of each system component.
2. **Performance Metrics:** Quantitatively measuring the accuracy and efficiency of both the AI models and the overall system.
3. **Comparison with Existing Solutions:** Benchmarking our results against published research to validate the project's effectiveness and novelty.

5.1 Testing Strategies

A multi-layered testing strategy was employed to ensure the robustness and reliability of the entire application.

The core AI models were evaluated using standard machine learning practices to ensure they generalize well to new, unseen data.

- **Dataset Splitting:** As detailed in the datasets for both detection and segmentation were strategically split into three distinct sets:
  - **Training Set (approx. 70%):** Used to train the models.
  - **Validation Set (approx. 10%):** Used during the training process to monitor the model's performance, tune hyperparameters, and trigger mechanisms like **Early Stopping** to prevent overfitting.
  - **Testing Set (approx. 20%):** A completely unseen dataset reserved for the final evaluation of the trained model's performance. All reported metrics are based on this set.

The backend RESTful API was rigorously tested using **Postman** to verify the functionality, security, and error handling of every endpoint.

- **Functionality Testing (Happy Path):** Each CRUD operation was tested to ensure it performed as expected. This included creating users, logging in, managing patients and assistants, and linking AI analysis results

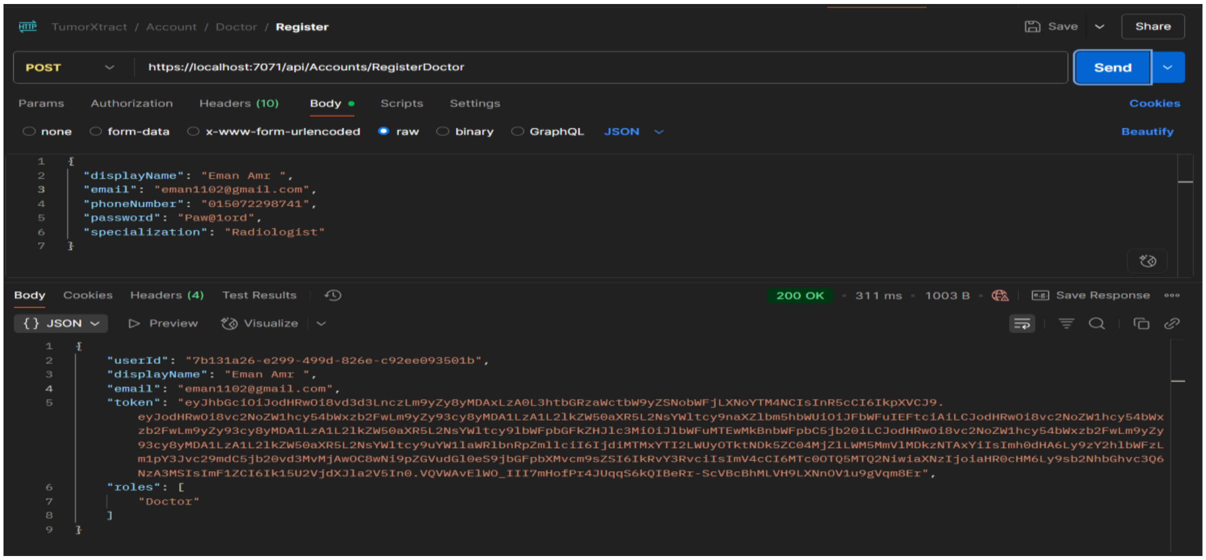

Fig. **Error! No text of specified style in document.**.9Successful User Registration with role ”Doctor”.

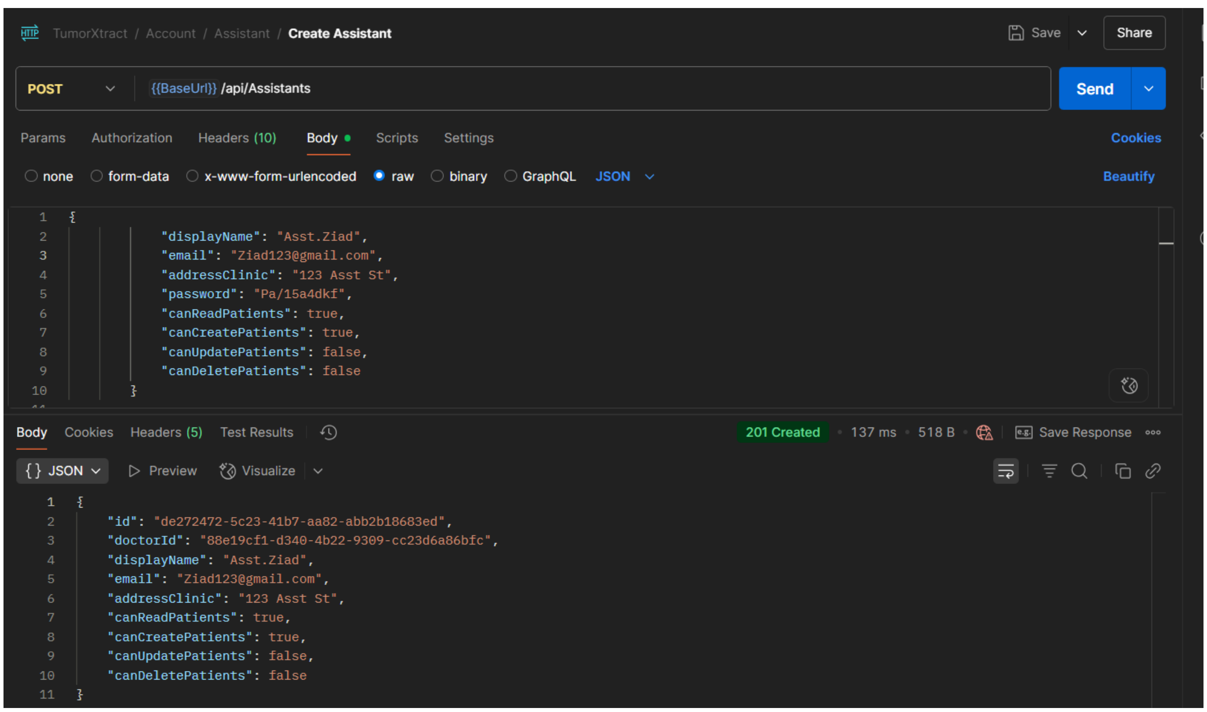

*Fig. **Error! No text of specified style in document.**.10new*

- **Security and Authorization Testing:** Security endpoints were tested for both successful and failed authentication attempts (Figures 5.4, 5.5). Furthermore, the role-based authorization was validated by testing assistant permissions, confirming that an assistant could or could not perform an action (e.g., update or delete a patient) based on the permissions granted by the doctor

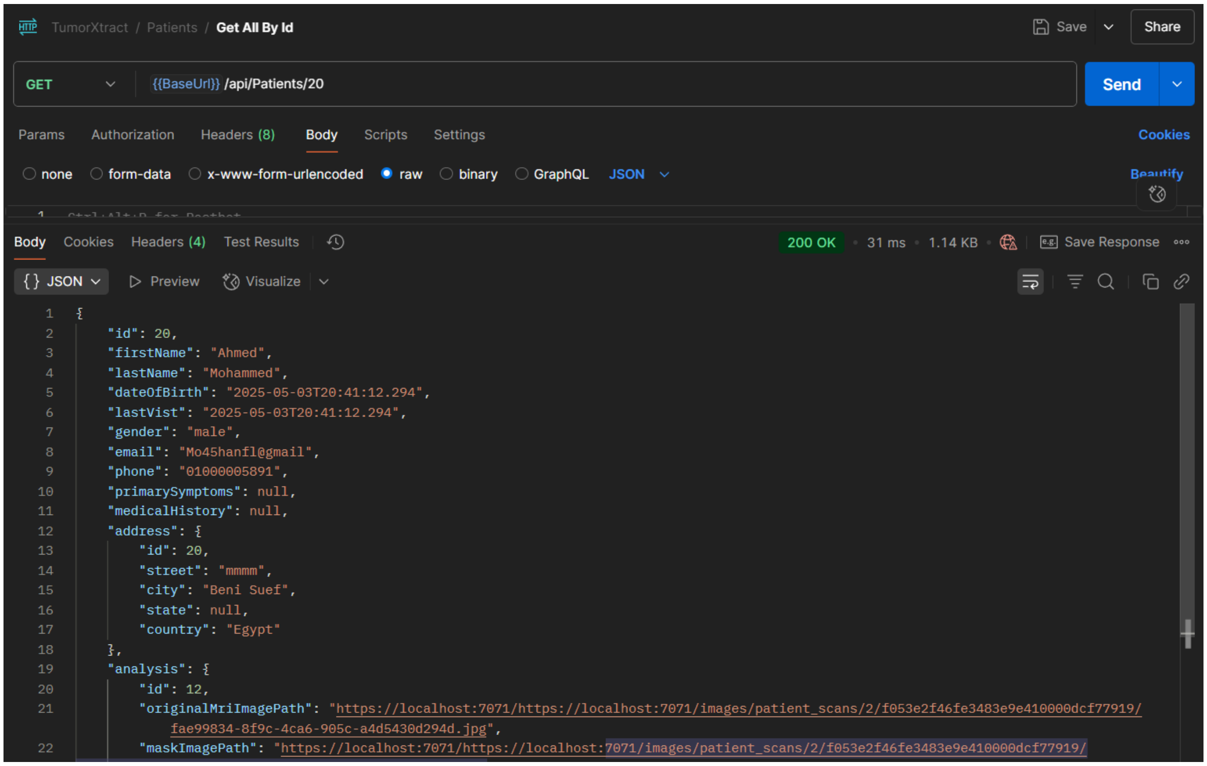

Fig. **Error! No text of specified style in document.**.11Get Patient by id because permission on.

- **Error Handling Testing:** The API's response to invalid or improper requests was tested to ensure graceful error handling. This included testing with bad requests ,requests for non-existent resources ,and confirming the system's ability to handle internal server errors.

The entire application was tested manually from a user's perspective to ensure all components were correctly integrated and the clinical workflow was seamless. The visual walkthrough in Chapter 6 serves as evidence of this successful end-to-end testing, covering the full user journey:

1. Navigating the public website.

2. Registering a new doctor account and logging in.
3. Managing the user profile and assistant accounts.
4. Creating a new patient record.
5. Uploading a patient's MRI scan for analysis.
6. Viewing the comprehensive AI-generated results, including the classification, confidence scores, and segmentation overlay.

5.2 Performance Metrics

System performance was evaluated using both AI model metrics and application-level metrics.

- **AI Model Performance:** The effectiveness of the deep learning models was measured using standard classification and segmentation metrics:
    - **Accuracy:** The percentage of total correct predictions. Our final detection model (EfficientNet) achieved an accuracy of **98.78%** on the test dataset.
    - **Precision:** The proportion of positive identifications that were actually correct, minimizing false positives.
    - **Recall (Sensitivity):** The proportion of actual positives that were correctly identified, minimizing false negatives.
    - **MCC (Matthews Correlation Coefficient):** A balanced measure that accounts for true/false positives and negatives, which is particularly useful for imbalanced datasets.

Segmentation Model (Attention U-Net):

  - The Attention U-Net achieved a Mean IOU of 82.88% and an overall accuracy of 99.35%, indicating a very high degree of overlap between the predicted tumor masks and the ground truth masks.

- **System Performance & Scalability:** The web application's performance was evaluated against the following Key Performance Indicators (KPIs):
  - **Response Time:** Initial page loads under 3 seconds and image analysis results returned to the user in under 10 seconds.
  - **Scalability:** The system was designed with a stateless backend API (using JWT for authentication) to support horizontal scaling. The initial design target was to handle up to 10 concurrent radiologists during peak hours.

5.3 Comparison with Existing Solutions

The performance of our TumorXtract system was benchmarked against models presented in recent academic literature. While many research papers focus solely on model accuracy, our project's primary contribution is the integration of a high-performing model into a complete, clinically-oriented platform.

Model/Study	Reported Accuracy	Scope
MRFO-CNN (Bose & Garg, 2024)	99.3%	Detection Model Only

UNet with Multi-Attention (Abboodi et al., 2024)	99%	Segmentation Model Only
EDN-SVM (Anantharajan et al., 2024)	97.93%	Detection Model Only
TumorXtract (Our System)	**98.78% ,**	**Integrated Detection, Segmentation, & Clinical Platform**

While some individual models report slightly higher accuracies, our system is highly competitive and provides a significant advantage by delivering these results within a functional, end-to-end application. Unlike the academic models, TumorXtract provides user authentication, patient data management, and a seamless workflow, bridging the gap between a research algorithm and a practical tool.

Chapter 6

Results & Discussion

6.1 Introduction

This chapter presents the functional results of the TumorXtract project. It showcases the implemented backend API's capabilities and discusses the implications of these results, demonstrating a successful translation of system design into a working prototype.

6.2 Summary of findings

The development phase culminated in several key achievements that form the core of the TumorXtract platform:

- **A Fully Functional Backend API:** A secure and robust backend API was successfully developed using ASP.NET Core. It effectively handles all core functionalities, including:
  - JWT-based authentication and role-based authorization for Doctors and Assistants.
  - Comprehensive CRUD operations for patient records.
  - Management of user profiles and assistant permissions.
  - Orchestration of the entire AI analysis workflow.
- **Successful Integration of the AI Pipeline:** The backend seamlessly communicates with the external Python-based AI service. It correctly forwards MRI images for analysis and processes the returned JSON data, which includes the tumor prediction, confidence scores, and base64-encoded segmentation mask and overlay images.

- Robust and Relational Data Management: The system effectively uses SQL Server and Entity Framework Core to persist data. Analysis results are temporarily stored before being permanently linked to a specific patient, creating a holistic and relational record for each case.

6.3 Interpretation of results

The functionality of the backend API is the cornerstone of the entire system. To demonstrate its successful implementation, extensive testing was performed using API testing tools like Postman. The figure below shows a successful test of the Doctor registration endpoint.

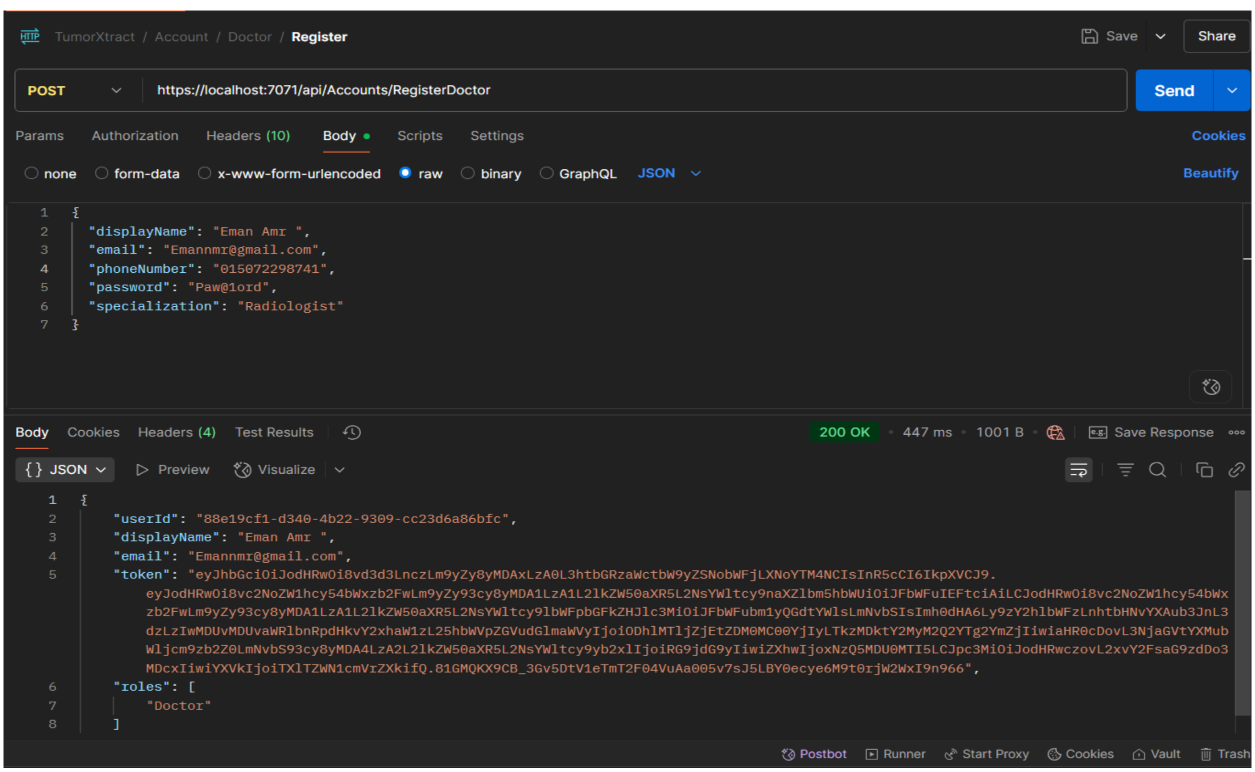

Fig. 6.1API Test for Doctor Registration Endpoint.

This result is significant because it validates several key system components simultaneously:

1. **Endpoint Functionality:** The /api/Accounts/RegisterDoctor endpoint is live and correctly processes incoming POST requests.
2. **Data Validation:** The system correctly validates the incoming JSON payload.
3. **Business Logic:** The user is successfully created in the database with a hashed password via ASP.NET Core Identity.
4. **Security Mechanism:** Upon successful registration, the API generates and returns a JSON Web Token (JWT). This token is essential for authenticating subsequent requests to protected endpoints, forming the basis of the system's security model.

This successful API call serves as a concrete proof-of-concept for the user management module, which is the gateway for clinicians to access all other features of the TumorXtract platform.

6.4 Limitations of the proposed solution.

While the project was a success, it is important to acknowledge its limitations, which provide clear avenues for future work.

- **Dataset Scope:** The models were trained and validated on a large, but publicly available, dataset. For real-world clinical deployment, the models would need to be re-validated, and potentially fine-tuned, on more diverse clinical data from different hospitals and imaging machines to ensure they are robust to variations in imaging protocols and patient demographics.
- **2D Image Analysis:** The current system processes MRI scans as a series of 2D slices. While effective, it does not perform a full 3D volumetric analysis. A 3D approach could provide a more

comprehensive understanding of the tumor's structure, volume, and spatial relationship with surrounding tissues.

- **Deployment Environment**: The current prototype uses the local file system for storing generated images (masks and overlays). A production-ready system would require a more robust and scalable solution, such as cloud-based object storage (e.g., Azure Blob Storage or AWS S3), to ensure data persistence, availability, and security.

Chapter 7

Conclusion & Future Work

7.1 Summary of contributions

This project makes a significant contribution by bridging the gap between academic AI research and practical clinical application. The primary contributions of TumorXtract are:

1. **A High-Performance, Dual-Model AI Pipeline:** We developed and validated a novel two-stage AI pipeline that first detects and classifies brain tumors using EfficientNet-B3 and then precisely segments them using Attention U-Net, achieving state-of-the-art accuracy and reliability.
2. **A Fully Integrated Clinical Web Platform:** We successfully designed and built a secure, robust, and user-friendly web application that operationalizes this AI technology. The platform provides a complete workflow for clinicians, including patient management, hierarchical user roles, and automated reporting.
3. **A Blueprint for Practical AI Integration:** The system's microservice architecture serves as a practical model for integrating computationally intensive AI tasks into responsive, real-world web applications without compromising user experience or system performance.

In essence, TumorXtract is more than an algorithm; it is a proof-of-concept for a complete, deployable system that can augment clinical decision-making and improve the efficiency of brain tumor diagnosis.

7.2 Possible improvements or extensions for future work

The current system provides a strong foundation for numerous future enhancements and research directions.

- **3D Volumetric Analysis:** The most immediate technical improvement would be to adapt the models to process full 3D MRI volumes instead of 2D slices. This would enable more accurate volume calculation and a better understanding of the tumor's three-dimensional structure.
- **Integration with Hospital Information Systems (HIS):** To be truly useful in a clinical setting, the system should be integrated with existing hospital infrastructure, such as Picture Archiving and Communication Systems (PACS) for direct image retrieval and Electronic Health Records (EHR) for seamless patient data synchronization.
- **Longitudinal Monitoring:** The platform could be extended to track tumor progression over time. By analyzing a series of scans from the same patient, a future model could automatically measure changes in tumor size and volume, providing valuable feedback on treatment effectiveness.
- **Predictive Analytics:** Beyond detection and segmentation, future AI models could be trained to predict other clinically relevant information, such as the tumor's genetic subtype, malignancy grade, or patient survival rates, directly from the MRI scans.
- **Full Clinical Trial and Deployment:** The ultimate future work is to move the system from a prototype to a clinically validated tool through

rigorous testing in a real-world hospital environment, gathering feedback from radiologists, and obtaining the necessary regulatory approvals.

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Appendices

This section provides supplementary materials that offer deeper technical insight and reference information for the TumorXtract project. It includes a list of abbreviations, a summary of API endpoints, sample code snippets, detailed system diagrams, a quick-start user guide, and information on the datasets used for model training.

List of Abbreviations

Word	**Abbreviation**	**Word**	**Abbreviation**
Two-Dimensional	2D	C#	C Sharp
Three-Dimensional	3D	CNN	Convolutional Neural Network
Adaptive Contrast Enhancement Algorithm	ACEA	CNS	Central Nervous System
Artificial Intelligence	AI	CRUD	Create, Read, Update, Delete
Application Programming Interface	API	CSS	Cascading Style Sheets

Computed Tomography	CT	ERD	Entity-Relationship Diagram
Dependency Injection	DI	FCM	Fuzzy C-Means
Deep Learning	DL	FK	Foreign Key
Data Transfer Object	DTO	FN	False Negative
Decision Tree	DT	FP	False Positive
Entity Framework	EF	FPN	Feature Pyramid Network
Graphical User Interface	GUI	HTTPS	HyperText Transfer Protocol Secure
HyperText Markup Language	HTML	IOU	Intersection over Union
HyperText Transfer Protocol	HTTP	JS	JavaScript
JavaScript Object Notation	JSON	ML	Machine Learning

JSON Web Token	JWT	MRI	Magnetic Resonance Imaging
Object-Relational Mapper	ORM	REST	Representational State Transfer
Portable Document Format	PDF	SQL	Secure Sockets Layer
Patient Health Information	PHI	TN	True Negative
		TP	True Positive

API Endpoints Summary

The following table summarizes the key RESTful API endpoints implemented in the ASP.NET Core backend.

HTTP Verb	Endpoint Path	Description	Authorized Role(s)
POST	/api/Account/Doctor/Register	Registers a new Doctor account.	public
POST	/api/Account/Login	Authenticates a user (Doctor or Assistant) and returns a JWT.	public

GET	/api/Account/GetProfile	Retrieves the profile of the currently logged-in user.	Doctor
PUT	/api/Account/UpdateProfile	Updates the profile of the currently logged-in user.	Doctor
GET	/api/Patients/{id}	Retrieves the details of a specific patient	Doctor, Assistant (Permitted)
Get	/api/Patients	Retrieves a paginated list of all patients for a Doctor.	Doctor, Assistant
Post	/api/Patients/CreatePatient	Creates a new patient record.	Doctor, Assistant (Permitted)
Put	/api/Patients/UpdatePatient/{id}	Updates an existing patient's record.	Doctor, Assistant (Permitted)
delete	/api/Patients/DeletePatient/{id}	Deletes a patient's record.	Doctor, Assistant (Permitted)
POST	/api/Analysis/Predict	Uploads an MRI scan and returns a	Doctor

		temporary analysis result.	
POST	/api/Patients/LinkAnalysis	Links a temporary analysis to a permanent patient record.	Doctor
GET	/api/Assistants	Retrieves a list of all assistants for the logged-in Doctor.	Doctor
POST	/api/Assistants/CreateAssistant	Creates a new Assistant account with specified permissions.	Doctor
PUT	/api/Assistants/UpdateAssistant/{id }	Updates an existing Assistant's permissions.	Doctor
DELE TE	/api/Assistants/DeleteAssistant/{id }	Deletes an Assistant's account.	Doctor

Sample API Request & Response Snippets

1. **Sample Request: Creating a New Patient**
   This JSON snippet shows the body of a POST request to the /api/Patients/CreatePatient endpoint.

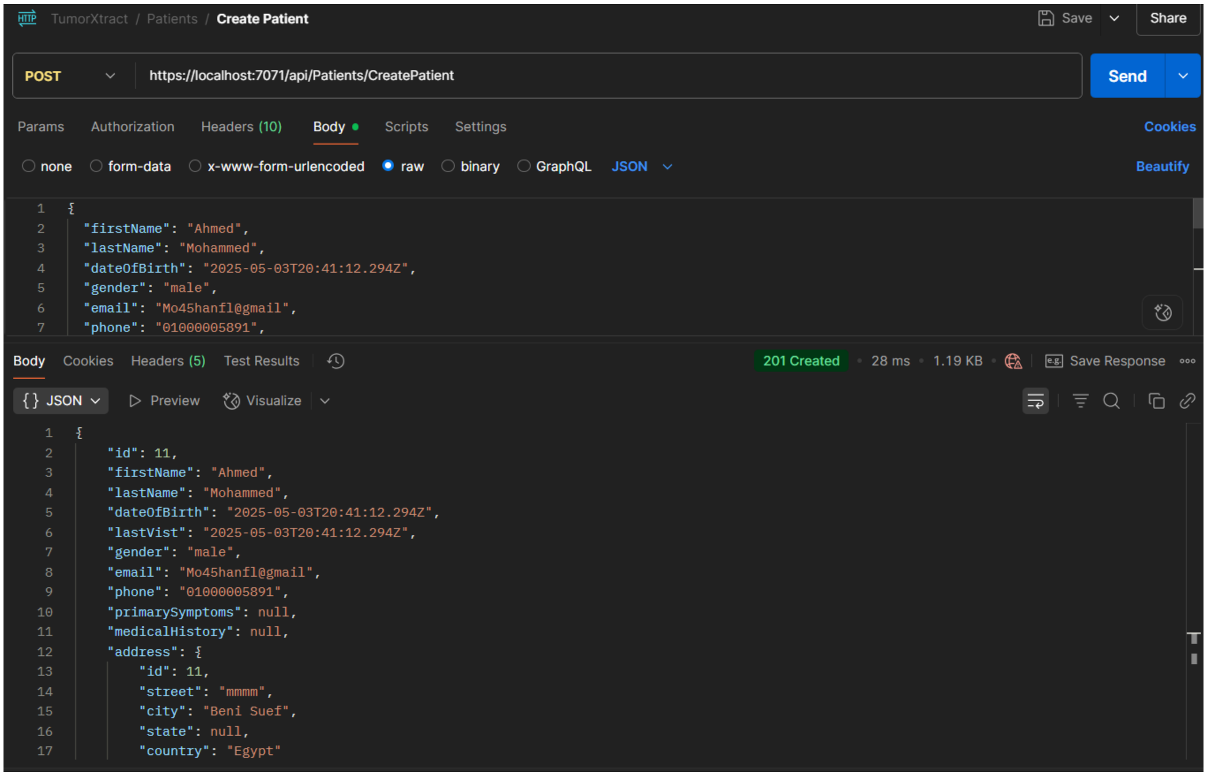
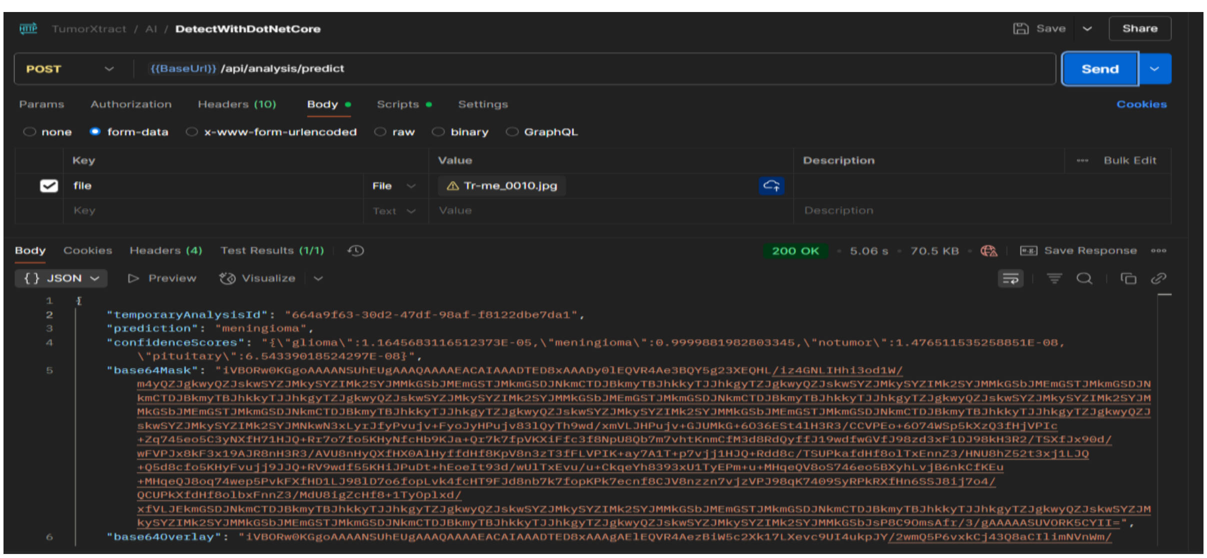


*Fig. **Error! No text of specified style in document.**.12Creating a New Patient*

Sample Response: AI Analysis Result

This JSON snippet shows the response from the /api/Analysis/Predict endpoint after a successful analysis.



Detailed System Diagrams

This section contains detailed technical diagrams that provide a deeper understanding of the system's architecture and database structure.

i. This diagram provides a static, object-oriented view of the system's backend, showing the main C# classes (e.g., Doctor, Patient), their attributes, methods, and the relationships between them

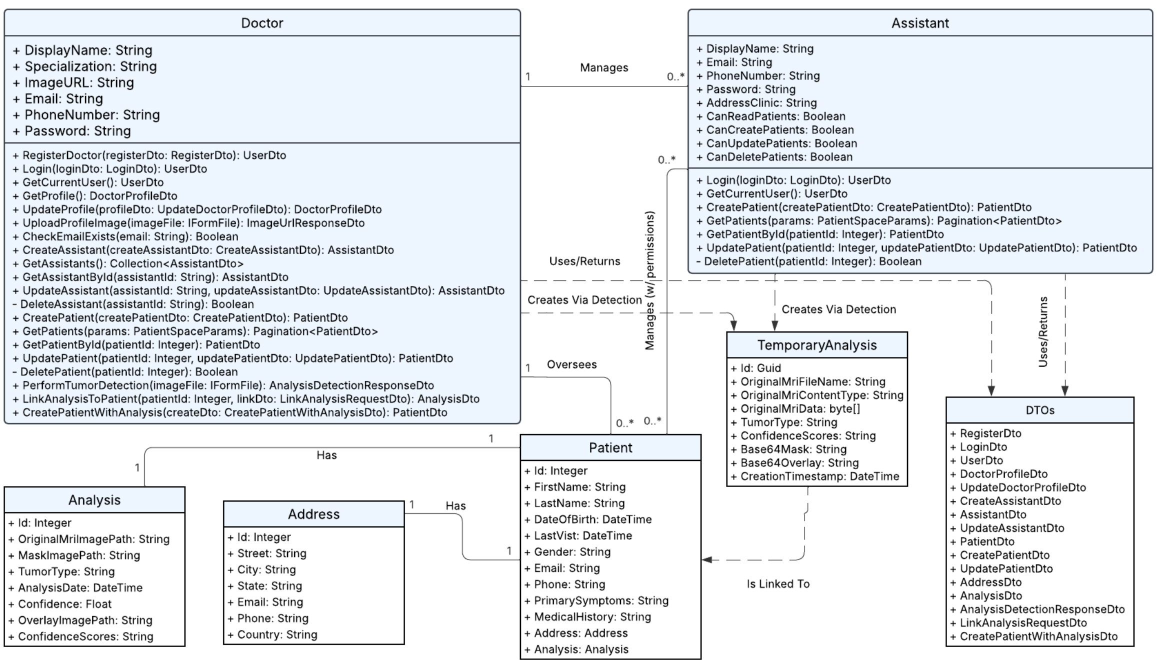


Fig. ***Error! No text of specified style in document.****.13Class Diagram*

ii. This diagram shows the logical structure of the SQL Server database, detailing the tables, their columns, primary and foreign key relationships, and data types.

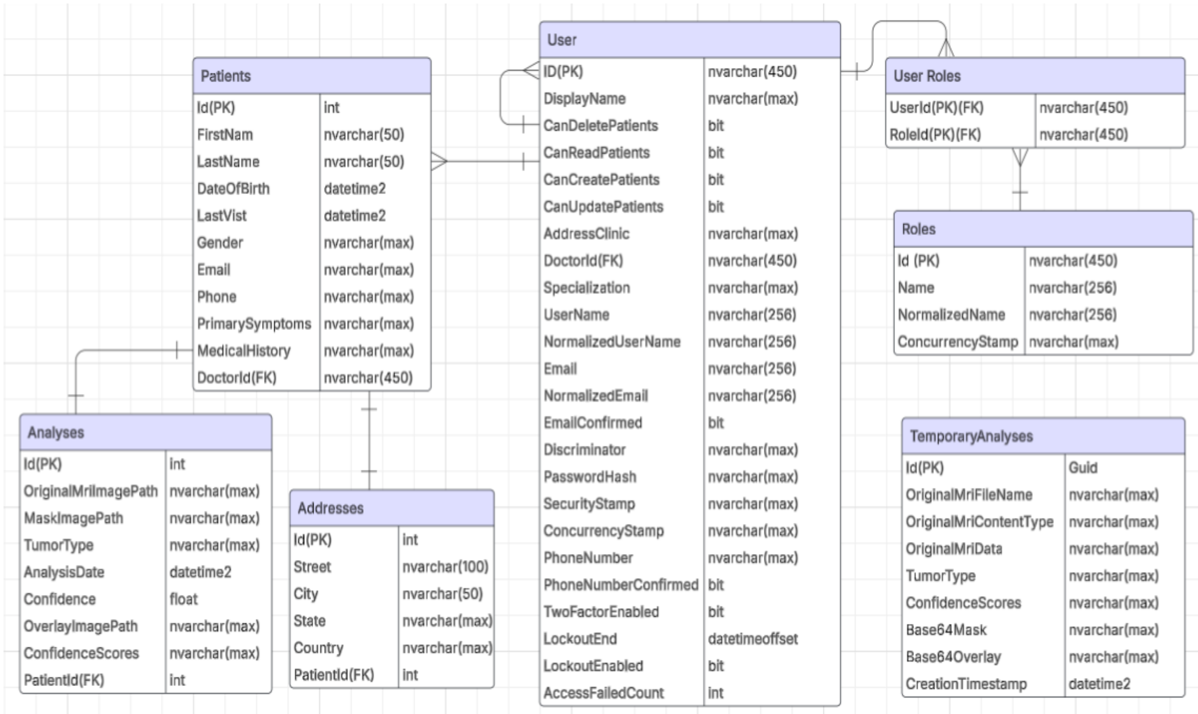


*Fig. **Error! No text of specified style in document.**.14Entity-Relationship Diagram (ERD)*

iii. This diagram illustrates the time-ordered sequence of interactions between the user, frontend, backend API, AI service, and database for key workflows like user login and performing a tumor analysis.