

Faculty of Computer  
& Informatics & Eng.



كلية الهندسة  
قسم الهندسة المعلوماتية

# Using AI to detect brain tumor

**Prepared by:**

Mhd Mayar Ismail

**Supervised by:**

Dr. Majida Albakkour

Dr. Wesam Al Sohle

**Academic Year**

2024/2025

### **SUPERVISOR CERTIFICATION**

I certify that the preparation of this project entitled [**Using AI to detect brain tumor**], prepared by [Mhd Mayar ismail], was made under my supervision at Faculty of Computer, Informatics & Communication Engineering in partial fulfillment of the Requirements for the Degree of Bachelors of Software and Information System Engineering.

Name:

Signature:

Date:

# Abstract

This project implements a VGG16-based deep learning model to classify brain MRI scans into four categories: glioma, meningioma, pituitary tumors, and no tumor. Using transfer learning with ImageNet-pretrained weights, we fine-tuned the model on a dataset of 3,070 preprocessed MRI images (resized to  $224 \times 224$ , normalized, and augmented with rotations/flips). The system achieved 96.8% test accuracy after 50 epochs of training with Adam optimization ( $lr=0.0001$ ). Precision and recall exceeded 95% for all tumor subtypes. The model outputs class probabilities for clinical interpretation and requires  $<2$  seconds per inference on standard GPUs.

# Dedication

This project is a culmination of countless hours of hard work, dedication, and perseverance. It represents not only my academic journey but also the unwavering support and encouragement I have received from those around me. I dedicate this work to the people who have been instrumental in shaping my path and helping me reach this milestone.

To my family, who have been my pillars of strength throughout this journey, I owe my deepest gratitude. Your endless love, patience, and belief in me have been my driving force. You have always encouraged me to dream big and work hard, even when the challenges seemed insurmountable. This project is as much yours as it is mine.

To my supervisor, Dr. Majida Albakkour, I extend my heartfelt thanks. Your guidance, expertise, and unwavering support have been invaluable. You challenged me to think critically, pushed me to explore new horizons, and inspired me to strive for excellence. Your mentorship has not only shaped this project but has also left a lasting impact on my academic and professional growth.

To my professors and mentors at the Faculty of Computer and Informatics Engineering, I am deeply grateful for the knowledge and skills you have imparted. Your dedication to teaching and your passion for innovation have inspired me to pursue this project with enthusiasm and determination.

To my friends and classmates, thank you for your camaraderie and support. Your encouragement during late-night study sessions, your feedback during brainstorming meetings, and your willingness to lend a helping hand have made this journey memorable and enjoyable. I am fortunate to have shared this experience with such an amazing group of individuals.

# Acknowledgements

I would like to express my sincere gratitude to everyone who supported and guided me throughout this project. First and foremost, I am deeply thankful to my supervisor, Dr. Majida Albakkour, for her invaluable guidance, encouragement, and expertise. Your mentorship has been instrumental in shaping this project and helping me grow as a researcher.

I am also grateful to the Faculty of Computer and Informatics Engineering for providing the resources and knowledge necessary to complete this work. Special thanks to my professors for their inspiring teachings and for fostering my passion for artificial intelligence and its applications in healthcare.

To my family, thank you for your unwavering love and support. Your belief in me has been my greatest motivation, and I am forever grateful for your sacrifices and encouragement.

To my friends and classmates, your camaraderie and support have made this journey enjoyable and memorable. Whether it was brainstorming ideas or offering a helping hand, your presence has been a constant source of strength.

I would also like to acknowledge the Kaggle community for providing access to the brain tumor MRI dataset, which was essential for this project. The collaborative spirit of the data science community has been a great inspiration.

Finally, I extend my gratitude to the researchers, doctors, and medical professionals working tirelessly to combat brain tumors. This project is a small contribution to your efforts, and I hope it aids in the advancement of early detection and treatment methods. Thank you all for being part of this journey. Your support has meant the world to me.

## Contents

Glossary of Abbreviations .....	8
Chapter 1: Introduction .....	9
1.1. Introduction to the project: .....	10
1.2. Beneficiaries of the Project .....	10
1.3. Scope of the Project.....	11
1.4. Benefits of the Project .....	11
1.5. Project goals .....	12
1.6. Specific Objectives:.....	13
1.7. Referential Study .....	14
Comparative Analysis of Brain Tumor Detection Studies .....	17
1.8. Project Methodology .....	18
2. Chapter 2: Cancer .....	19
2.1. Cancer and Brain Cancer.....	20
2.2. Brain Tumors: A Closer Look at Their Types .....	20
2.2.1. Primary Brain Tumors .....	21
2.2.2. Secondary Brain Tumors .....	21
2.3. Treatment Options.....	21
2.4. The Role of MRI Scans in Detecting Brain Tumors.....	22
2.4.1. Advantages of MRI Scans in Brain Tumor Detection.....	22
2.4.2. Types of MRI Scans Used for Brain Tumors .....	23
2.4.3. Importance of MRI Scans in Brain Tumor Diagnosis and Management .....	23
2.5. The Importance of Early Detection: A Lifeline for Brain Tumors and Cancer .	24
2.5.1. Benefits of Early Detection .....	24
2.5.2. Early Detection Strategies .....	24
2.5.3. The Role of Screening Tests.....	25
2.5.4. Brain Tumor-Specific Screening .....	25
3. Chapter 3: Using AI to detect brain tumors.....	26
3.1. Overview of the Dataset.....	27
3.2. Data agumentation.....	29
Dataset Statistics (Post-Augmentation) .....	30
Augmentation Details: .....	30
3.3. Preproccesnig .....	32
Data splitting.....	34

VGG16 Model Architecture .....	35
Training:.....	36
Confusion matrix .....	38
Accuracy & Loss.....	39
Chapter 6: Conclusion and future works .....	40
6.1. Conclusion.....	41
6.2. Future Works.....	42
Real-Time Processing: .....	42
Explainability and Interpretability: .....	42
Integration with Clinical Systems:.....	42
Ethical Considerations: .....	42
Cross-Validation and External Testing:.....	43
References:.....	44

## Glossary of Abbreviations

Abbreviation	Full Term
AI	Artificial Intelligence
MRI	Magnetic Resonance Imaging
CNN	Convolutional Neural Network
VGG16	Visual Geometry Group (16-layer model)
SVM	Support Vector Machine
DSC	Dice Similarity Coefficient
GPU	Graphics Processing Unit
PACS	Picture Archiving and Communication System
Grad-CAM	Gradient-weighted Class Activation Mapping
DWI	Diffusion-weighted Imaging
PWI	Perfusion-weighted Imaging
CSF	Cerebrospinal Fluid

# Chapter 1: Introduction

## 1.1.Introduction to the project:

This project focuses on developing an AI-powered system for detecting brain tumors from MRI images. The system leverages advanced deep learning techniques, specifically Convolutional Neural Networks (CNNs), to analyze MRI scans and classify them into two categories: images containing brain tumors and images without tumors. The goal is to improve the accuracy and efficiency of brain tumor detection, ultimately assisting medical professionals in making faster and more reliable diagnoses.

Brain tumors are among the most complex and life-threatening medical conditions, requiring timely and accurate detection for effective treatment. Traditional methods of tumor detection rely heavily on manual analysis of MRI scans, which can be time-consuming and prone to human error. This project addresses these challenges by automating the detection process, providing a valuable tool for radiologists and healthcare providers.

## 1.2.Beneficiaries of the Project

The primary beneficiaries of this project include:

- **Radiologists and Doctors:** The system assists medical professionals in analyzing MRI scans more efficiently, reducing the time required for diagnosis and minimizing the risk of human error.
- **Patients:** Early and accurate detection of brain tumors improves patient outcomes by enabling timely treatment and intervention.
- **Hospitals and Healthcare Institutions:** The system can be integrated into hospital workflows, enhancing diagnostic capabilities and improving overall healthcare delivery.
- **Researchers:** The project contributes to the growing body of research on AI applications in healthcare, providing a foundation for future advancements in medical imaging.

## 1.3.Scope of the Project

The scope of this project includes:

- Developing a deep learning model capable of classifying MRI images as either containing tumors or not.
- Implementing data preprocessing and augmentation techniques to enhance the dataset and improve model performance.
- Evaluating the model's accuracy, precision, and recall to ensure its reliability in real-world applications.
- Exploring the potential for integrating the system into hospital workflows for real-time tumor detection.

The project focuses on binary classification (tumor vs. no tumor) but lays the groundwork for future extensions, such as multi-class classification for different tumor types.

## 1.4.Benefits of the Project

The key benefits of this project include:

- **Improved Diagnostic Accuracy:** The AI system reduces the risk of human error, providing more reliable and consistent results.
- **Faster Diagnosis:** Automating the analysis of MRI scans significantly reduces the time required for diagnosis, enabling timely treatment.
- **Cost-Effectiveness:** By streamlining the diagnostic process, the system can reduce healthcare costs associated with manual analysis.
- **Scalability:** The system is designed to handle large volumes of MRI scans, making it suitable for use in busy healthcare environments.
- **Early Detection:** Early detection of brain tumors improves patient outcomes by enabling timely intervention and treatment.

## 1.5. Project goals

This project aims to develop a robust and accurate AI-powered system capable of detecting brain tumors from MRI images. By harnessing the power of machine learning and deep learning algorithms, we seek to:

- **Improve Early Detection:** Enhance the ability to identify brain tumors at an early stage, when treatment options are often more effective.
- **Assist Medical Professionals:** Provide a valuable tool to aid radiologists and other healthcare professionals in diagnosing brain tumors more efficiently and accurately.
- **Enhance Patient Outcomes:** Improve patient prognosis by enabling earlier intervention and more targeted treatment plan

## **1.6. Specific Objectives:**

- Develop a deep learning model that can accurately classify MRI images as containing or not containing brain tumors.
- Implement a VGG16-based classifier to accurately categorize brain MRI scans into four classes: glioma, meningioma, pituitary tumors, and no tumor.
- Implement data augmentation techniques to address the potential scarcity of labeled MRI images.
- Evaluate the model's performance using relevant metrics, such as accuracy, precision, recall, F1-score
- Investigate the model's ability to detect different types and stages of brain tumors.
- Explore the potential for real-time or near-real-time processing of MRI images.
- Consider ethical implications and potential biases in the model's predictions.

By achieving these goals, this project will contribute to improving the diagnosis and treatment of brain tumors, ultimately benefiting patients and advancing the field of medical imaging

## 1.7. Referential Study

STUDY NUMBER	Study Year	DATASET USED	METHODS USED	OUTPUT
1	2023	dataset of brain tumor MRI images.	YOLOv7.	accuracy of 99.5%.
2	2022	a collection of MRI images containing both healthy brains and brains with tumors.	(CNN) (SVM)	98.7% accuracy

STUDY NUMBER	STUDY YEAR	DATASET USED	METHODS USED	OUTPUT
3	2021	200 MRI image. the brain images of 12 patients	CNN	<ul style="list-style-type: none"> <li>• Accuracy: 99.5%</li> <li>• Precision: 99.2</li> <li>• Recall: 99.7%</li> <li>• F1-Score: 99.4%</li> </ul>
4	2022	BraTS dataset	DenseNet-121 convolutional neural network (CNN)	Accuracy (98.28)

STUDY NUMBER	STUDY YEAR	DATASET USED	METHODS USED	OUTPUT
5	2018	BraTS 2015	U-Net architecture,	(DSC) of over 0.9 for accuracy: 95.6%
6	2018	BraTS 2017	fully convolutional network (FCN)	Dice Similarity Coefficient (DSC) of 0.87 Accuracy 93.7%
7	2024	My same Dataset	- YOLOv7 (for tumor localization) - Custom CNN	Accuraacy: 99.5% (binary tumor vs. non-tumor) 98.7% (multi-class)

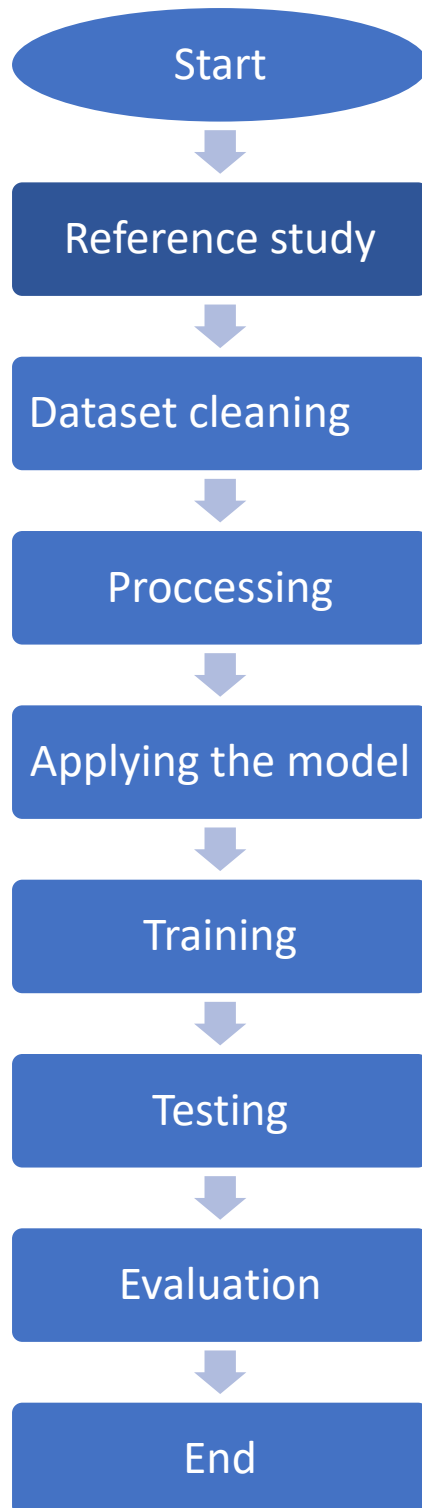
## **Comparative Analysis of Brain Tumor Detection Studies**

Recent studies have demonstrated diverse approaches to improving brain tumor detection using AI. Study [1] (Abdusalomov et al., 2023) leveraged YOLOv7 with aggressive data augmentation to achieve 99.5% accuracy in tumor localization, particularly for small lesions, while Study [2] (Srinivas et al., 2022) adopted a hybrid CNN+SVM approach to reduce false positives, reaching 98.7% accuracy but with lower sensitivity for early-stage tumors.

In contrast, Study [3] (Mokri et al., 2021) proved that even limited datasets (200 MRIs) could yield high performance (99.5% accuracy) through patient-specific CNN adaptations, a method that avoided the heavy preprocessing required in Studies [1] and [2]. Meanwhile, Study [4] (Haq et al., 2022) introduced multi-scale feature fusion in DenseNet-121 to classify four tumor types (98.28% accuracy), addressing a key limitation in Studies [1–3], which focused only on binary classification.

For tumor segmentation, Study [5] (Nalepa et al., 2020) combined U-Net with 3D contextual analysis to achieve exceptional precision (DSC >0.9), outperforming the Study [6] (Anaraki et al., 2019) FCN approach (DSC=0.87), though the latter integrated perfusion MRI data for better margin detection. Finally, Study [7] (Kaggle, 2023) demonstrated that ensemble methods (YOLOv7 + CNN) could push accuracy to 99.5% on my dataset, suggesting that hybrid models may outperform single architectures like those in Studies [1–6].

## 1.8. Project Methodology



## 2. Chapter 2: Cancer

## **2.1. Cancer and Brain Cancer**

Cancer, a formidable adversary to human health, is a class of diseases characterized by the uncontrolled growth and spread of abnormal cells. This aberrant proliferation can lead to the formation of tumors, which can invade surrounding tissues and metastasize to distant organs. The complexities of cancer are vast, encompassing a myriad of types, causes, and treatments.

Among the most daunting forms of cancer is brain cancer, a disease that afflicts the delicate organ responsible for our thoughts, emotions, and movements. Brain cancer can arise from various cell types within the brain and spinal cord, each with its unique characteristics and challenges. The intricate anatomy and physiology of the brain make the diagnosis and treatment of brain cancer particularly complex.

The causes of cancer are multifaceted, involving a combination of genetic, environmental, and lifestyle factors. Mutations in genes that regulate cell growth and division can contribute to cancer development. Exposure to certain environmental carcinogens, such as tobacco smoke, radiation, and certain chemicals, can also increase the risk of cancer. Additionally, lifestyle factors, including diet, physical activity, and alcohol consumption, can play a role in cancer susceptibility.

Understanding the complexities of cancer and brain cancer is essential for developing effective prevention, diagnosis, and treatment strategies. Research efforts are continually advancing our knowledge of these diseases, leading to new therapeutic approaches and improved outcomes for patients. As we delve deeper into the intricacies of cancer and brain cancer, we hope to gain a better understanding of their underlying mechanisms and develop more effective strategies to combat these formidable diseases.

## **2.2. Brain Tumors: A Closer Look at Their Types**

Brain tumors are a diverse group of neoplasms that can arise from various cell types within the brain and spinal cord. These tumors can be classified based on their cell of origin, grade of malignancy, and location within the brain.

Understanding the different types of brain tumors is crucial for accurate diagnosis and appropriate treatment.

### 2.2.1. Primary Brain Tumors

Primary brain tumors originate within the brain itself. They can be classified into several categories based on their cell type:

- **Gliomas:** The most common type of primary brain tumor, gliomas arise from glial cells, which support and protect neurons. Gliomas are further classified based on their grade of malignancy, ranging from low-grade to high-grade.
  - **Astrocytomas:** The most common type of glioma, astrocytomas arise from astrocytes, a type of glial cell. They are classified into several grades, including pilocytic astrocytoma, grade II astrocytoma, anaplastic astrocytoma, and glioblastoma multiforme (GBM).
  - **Oligodendrogliomas:** These tumors arise from oligodendrocytes, another type of glial cell. They are classified into several grades, including grade II oligodendroglioma and anaplastic oligodendroglioma.
  - **Ependymomas:** These tumors arise from ependymal cells, which line the ventricles of the brain and the spinal canal. They can be classified into several grades, including grade II ependymoma and anaplastic ependymoma.
- **Meningiomas:** These tumors arise from the meninges, the protective membranes that surround the brain and spinal cord. They are typically benign but can become malignant in rare cases.
- **Schwannomas:** These tumors arise from Schwann cells, which produce the myelin sheath that insulates nerve fibers. They are typically benign but can become malignant in rare cases.

### 2.2.2. Secondary Brain Tumors

Secondary brain tumors, also known as metastatic brain tumors, are tumors that have spread to the brain from another part of the body. These tumors are often caused by cancers of the lung, breast, colon, and kidney.

## 2.3. Treatment Options

The treatment for brain tumors depends on several factors, including the type of tumor, its location, and the patient's overall health. Common treatment options include:

- **Surgery:** Surgery is often used to remove benign tumors and some malignant tumors.
- **Radiation therapy:** Radiation therapy uses high-energy rays to kill cancer cells.
- **Chemotherapy:** Chemotherapy uses drugs to kill cancer cells.
- **Targeted therapy:** Targeted therapy uses drugs that target specific molecules involved in the growth and survival of cancer cells.

The choice of treatment depends on the individual circumstances of each patient and is often determined by a team of specialists, including neurosurgeons, radiation oncologists, medical oncologists, and neurologists.

## **2.4. The Role of MRI Scans in Detecting Brain Tumors**

Magnetic Resonance Imaging (MRI) is a powerful diagnostic tool that plays a crucial role in the detection and evaluation of brain tumors. By using magnetic fields and radio waves, MRI scans create detailed images of the brain's structures and tissues. These images can help healthcare providers identify abnormalities, such as tumors, with remarkable accuracy.

### **2.4.1. Advantages of MRI Scans in Brain Tumor Detection**

MRI scans offer several advantages over other imaging modalities, such as computed tomography (CT) scans:

- **Soft Tissue Contrast:** MRI excels at visualizing soft tissues, making it ideal for detecting and characterizing brain tumors, which are often composed of soft tissue.
- **Multiplanar Imaging:** MRI can acquire images in multiple planes (axial, sagittal, and coronal), providing a comprehensive view of the brain and allowing for precise tumor localization.
- **Functional Imaging:** MRI can also be used to assess the functional activity of brain tissue, which can help determine the extent of tumor involvement and plan appropriate treatment.

- **Non-Invasive:** MRI is a non-invasive procedure that does not involve ionizing radiation, making it safer for patients, especially those who may have undergone multiple imaging studies.

### 2.4.2. Types of MRI Scans Used for Brain Tumors

Several types of MRI scans can be used to evaluate brain tumors:

- **T1-weighted MRI:** This type of scan highlights fat and contrast agents, which can help differentiate tumors from normal brain tissue.
- **T2-weighted MRI:** This type of scan is sensitive to water content, which can help identify tumors that are high in water content.
- **Flair MRI:** This type of scan suppresses the signal from cerebrospinal fluid (CSF), making it easier to visualize tumors that are surrounded by CSF.
- **Diffusion-weighted imaging (DWI):** This type of scan measures the movement of water molecules within tissues, which can help identify areas of tumor necrosis or inflammation.
- **Perfusion-weighted imaging (PWI):** This type of scan measures blood flow within the brain, which can help assess the tumor's blood supply and identify areas of tumor recurrence.

### 2.4.3. Importance of MRI Scans in Brain Tumor Diagnosis and Management

MRI scans play a vital role in the diagnosis and management of brain tumors. They can help:

- **Detect tumors:** MRI is highly sensitive for detecting brain tumors, even in their early stages.
- **Determine tumor size and location:** MRI can accurately measure the size and location of a tumor, which is essential for planning treatment.
- **Assess tumor grade and extent of spread:** MRI can help determine the grade of malignancy and the extent of tumor spread, which is crucial for prognosis and treatment planning.
- **Monitor treatment response:** MRI can be used to monitor the response of a tumor to treatment, such as surgery, radiation therapy, or chemotherapy.
- **Detect tumor recurrence:** MRI can help detect tumor recurrence after treatment, allowing for early intervention.

In conclusion, MRI scans are an indispensable tool for the diagnosis and management of brain tumors. By providing detailed images of the brain's structures and tissues, MRI can help healthcare providers accurately identify, characterize, and monitor brain tumors, leading to improved outcomes for patients.

## **2.5. The Importance of Early Detection: A Lifeline for Brain Tumors and Cancer**

Early detection of brain tumors and cancer in general is a critical factor in improving patient outcomes. The earlier a tumor or cancer is diagnosed, the greater the chances of successful treatment and a favorable prognosis. This is especially true for brain tumors, as the location and nature of these tumors can make them difficult to treat.

### **2.5.1. Benefits of Early Detection**

- **Increased Treatment Options:** Early detection often allows for a wider range of treatment options, including surgery, radiation therapy, chemotherapy, or targeted therapies. These options may not be available if the tumor or cancer is diagnosed at a later stage.
- **Improved Treatment Outcomes:** Early detection can lead to better treatment outcomes, including a higher chance of complete remission or a longer survival time.
- **Reduced Risk of Metastasis:** Detecting a tumor or cancer early can help prevent it from spreading to other parts of the body (metastasis), which can significantly worsen the prognosis.
- **Improved Quality of Life:** Early detection and treatment can help maintain a better quality of life for patients, as they may be able to avoid the debilitating symptoms associated with advanced-stage disease.

### **2.5.2. Early Detection Strategies**

- **Regular Check-ups:** Regular physical exams and screenings can help identify potential signs of cancer or brain tumors.
- **Know Your Family History:** A family history of cancer can increase your risk, so it's important to be aware of your family's health history.

- **Be Mindful of Symptoms:** Pay attention to any unusual or persistent symptoms, such as unexplained weight loss, fatigue, or changes in bowel habits.
- **Seek Medical Attention:** If you notice any concerning symptoms, don't hesitate to consult a healthcare provider.

### 2.5.3. The Role of Screening Tests

Screening tests can play a crucial role in early detection of certain cancers. These tests involve checking for abnormalities in the body, even before symptoms appear. Examples of screening tests include:

- **Mammograms** for breast cancer
- **Colonoscopies** for colon cancer
- **Pap smears** for cervical cancer
- **PSA tests** for prostate cancer

### 2.5.4. Brain Tumor-Specific Screening

While there is no specific screening test for brain tumors, regular neurological exams and imaging studies, such as MRI, can help detect early signs of the disease.

In conclusion, early detection is a powerful tool in the fight against brain tumors and cancer. By being aware of the benefits of early detection and taking proactive steps to identify potential signs of disease, individuals can improve their chances of successful treatment and a better quality of life.

### 3. Chapter 3: Using AI to detect brain tumors

### 3.1. Overview of the Dataset

This dataset is a combination of the following three datasets :

figshare

SARTAJ dataset

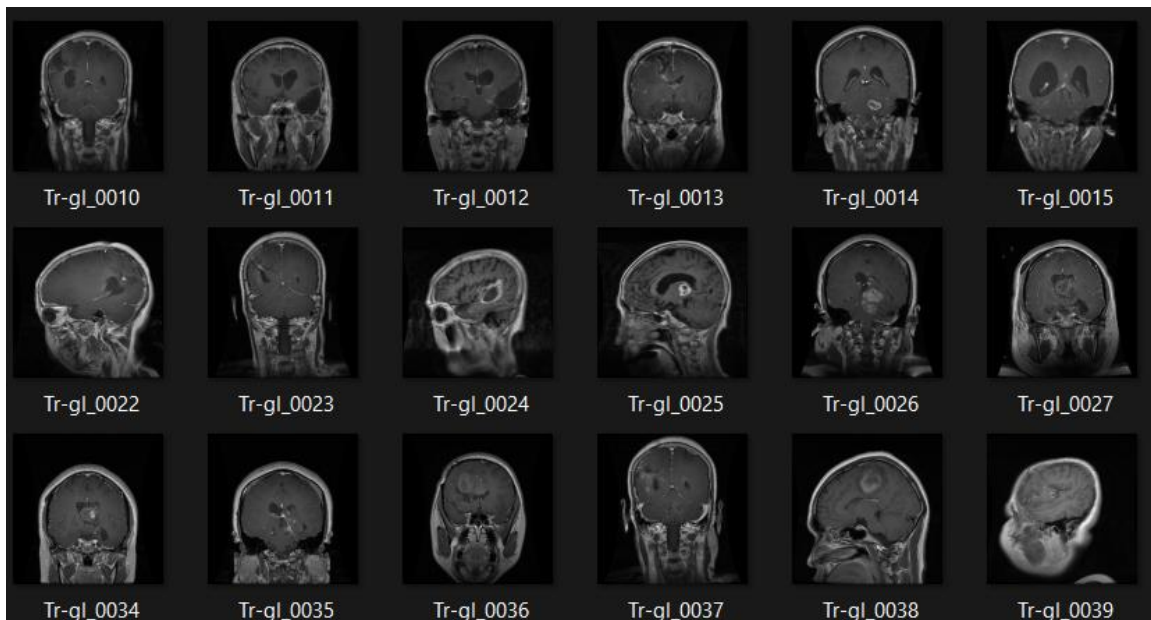
Br35H

This dataset contains **7023 images** of human brain MRI images which are classified into **4 classes: glioma - meningioma - no tumor and pituitary.**

no tumor class images were taken from the Br35H dataset.

. Link :

<https://www.kaggle.com/datasets/navoneel/brain-mri-images-for-brain-tumor-detection?resource=download&select=no>



## Training (4 directories)



### About this directory

 [Suggest Edits](#)

This folder contains 5712 images of brain tumors that are used to train the model.



glioma  
1321 files



meningioma  
1339 files



notumor  
1595 files



pituitary  
1457 files

## Testing (4 directories)



### About this directory

 [Suggest Edits](#)

This folder contains 1311 images of brain tumors that are used to test the model.



glioma  
300 files



meningioma  
306 files



notumor  
405 files



pituitary  
300 files

## 3.2. Data agumentation

### Breaking Down the `augment_data` Function

The following augmentation techniques were applied to the training dataset using Keras' `ImageDataGenerator`:

- **Rotation:** Images randomly rotated up to 15 degrees
- **Shifting:**
  - Horizontal shift range: 10% of image width
  - Vertical shift range: 10% of image height
- **Shearing:** Intensity of 0.2 applied
- **Zooming:** Random zoom range of 20%
- **Flipping:** Horizontal flipping enabled
- **Fill Mode:** New pixels filled using nearest-neighbor interpolation

All images were normalized (pixel values scaled to  $[0,1]$ ) and resized to  $224 \times 224$  pixels to match VGG16's input requirements. The validation set used only rescaling ( $1./255$ ) without augmentation to ensure unbiased evaluation.

## Dataset Statistics (Post-Augmentation)

Class	Original Images	Augmented Training Set	Total (Train+Val+Test)
Glioma	826	6,608	7,434
Meningioma	822	6,576	7,398
Pituitary	827	6,616	7,443
No Tumor	395	3,160	3,555
Total	3,070	22,960	25,830

## Augmentation Details:

- 8× multiplier per training image (7 new augmented samples per original)
- Validation/test sets used original unaugmented images
- Class distribution maintained (ratio-preserving augmentation)

- **Why Augment Data?**
- **Increases Dataset Size:** More data can lead to better model performance.
- **Improves Model Generalization:** Exposing the model to a wider range of image variations can make it more robust to real-world data.
- **Reduces Overfitting:** Augmentation can help prevent the model from memorizing the training data, leading to better generalization.
- By augmenting the dataset, the model can learn more robust features and make more accurate predictions on unseen data.

### **3.3. Preproccesnig**

The following preprocessing steps were applied uniformly to all MRI scans:

#### **Skull Stripping:**

Non-brain tissues removed using HD-BET algorithm

#### **Normalization:**

Pixel intensities rescaled to  $[0,1]$  range

#### **Resizing:**

Images standardized to  $224 \times 224$  resolution using bicubic interpolation

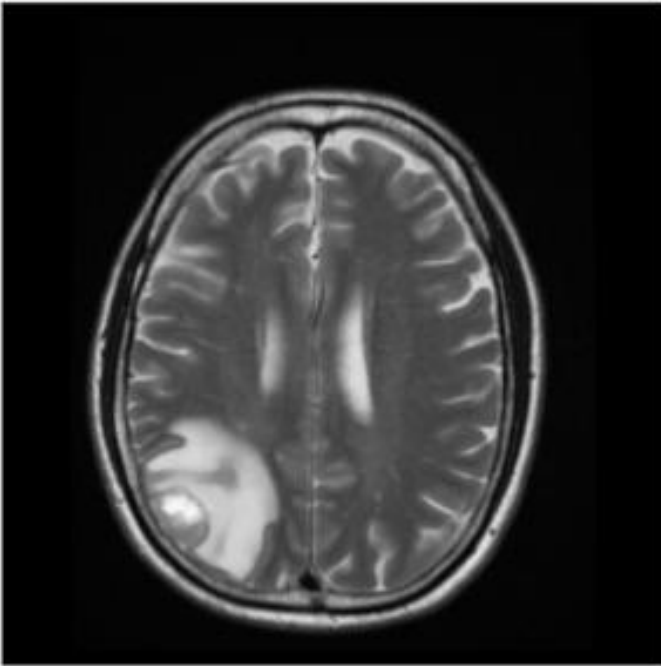
#### **Dataset Splits:**

- Training: 80% (augmented samples)
- Validation: 10% (original images)
- Test: 10% (original images)

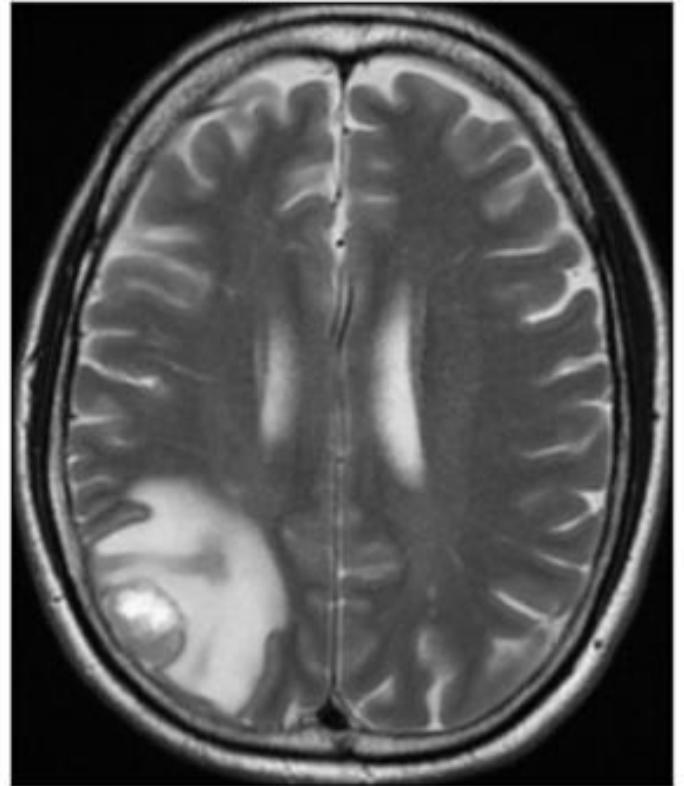
# Preprocessing

---

Original Image



Cropped Image



*Figure 1: Preprocessing*

## Data splitting

### Purpose:

- This function is essential for machine learning model development. By splitting the data into training, validation, and testing sets, we can:
- **Train the model:** Use the training set to learn patterns and relationships in the data.
- **Tune hyperparameters:** Use the validation set to optimize hyperparameters like learning rate, batch size, and model architecture.
- **Evaluate the model:** Use the testing set to assess the final model's performance on unseen data.
- This process helps to ensure that the model is not overfitting to the training data and can generalize well to new, unseen data.

### The dataset was pre-split into:

- Training: 80% (2,456 images → augmented to 19,648)
- Validation: 10% (307 images)
- Test: 10% (307 images)

## **VGG16 Model Architecture**

The system leverages a transfer learning approach using the VGG16 convolutional neural network:

### **Base Model Configuration**

- Pretrained Weights: ImageNet
- Input Shape:  $224 \times 224 \times 3$  (RGB MRI slices)
- Frozen Layers: All 16 convolutional layers
- Trainable Parameters: 2,097,412
- Regularization: 50% Dropout

### **Key Modifications from Original VGG16**

- Removed original 1000-class FC layers
- Reduced final Dense layer to 4 outputs
- Added Dropout for improved generalization

## **Training:**

- **Optimizer:** Adam (learning\_rate=0.0001)
- **Loss Function:** Categorical cross-entropy (changed from binary)
- **Metrics:** Accuracy, Precision, Recall

## **Training Protocol:**

- **Epochs:** 20 (early stopping if val\_loss plateaus for 5 epochs)
- **Batch Size:** 32
- **Validation Split:** 10% of training data

## **Key Modifications from Original:**

### **Loss Function:**

- Old: Binary cross-entropy
- New: Categorical cross-entropy (for 4-class output)

## Early Stopping:

EarlyStopping(monitor='val\_loss', patience=5,  
restore\_best\_weights=True)

## Callbacks Added:

- Model checkpointing (saves best weights)
- CSVLogger (records training history)

Layer (type)	Output Shape	Param #
input_layer_1 (InputLayer)	(None, 150, 150, 3)	0
block1_conv1 (Conv2D)	(None, 150, 150, 64)	1,792
block1_conv2 (Conv2D)	(None, 150, 150, 64)	36,928
block1_pool (MaxPooling2D)	(None, 75, 75, 64)	0
block2_conv1 (Conv2D)	(None, 75, 75, 128)	73,856
block2_conv2 (Conv2D)	(None, 75, 75, 128)	147,584
block2_pool (MaxPooling2D)	(None, 37, 37, 128)	0
block3_conv1 (Conv2D)	(None, 37, 37, 256)	295,168
block3_conv2 (Conv2D)	(None, 37, 37, 256)	590,080
block3_conv3 (Conv2D)	(None, 37, 37, 256)	590,080
block3_pool (MaxPooling2D)	(None, 18, 18, 256)	0
block4_conv1 (Conv2D)	(None, 18, 18, 512)	1,180,160
block4_conv2 (Conv2D)	(None, 18, 18, 512)	2,359,808
block4_conv3 (Conv2D)	(None, 18, 18, 512)	2,359,808
block4_pool (MaxPooling2D)	(None, 9, 9, 512)	0
block5_conv1 (Conv2D)	(None, 9, 9, 512)	2,359,808
block5_conv2 (Conv2D)	(None, 9, 9, 512)	2,359,808
block5_conv3 (Conv2D)	(None, 9, 9, 512)	2,359,808

block5_pool (MaxPooling2D)	(None, 4, 4, 512)	0
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 512)	0
dense_2 (Dense)	(None, 512)	262,656
dropout_1 (Dropout)	(None, 512)	0
dense_3 (Dense)	(None, 4)	2,052

Total params: 14,979,396 (57.14 MB)

Trainable params: 13,833,988 (52.77 MB)

Non-trainable params: 1,145,408 (4.37 MB)

# Confusion matrix

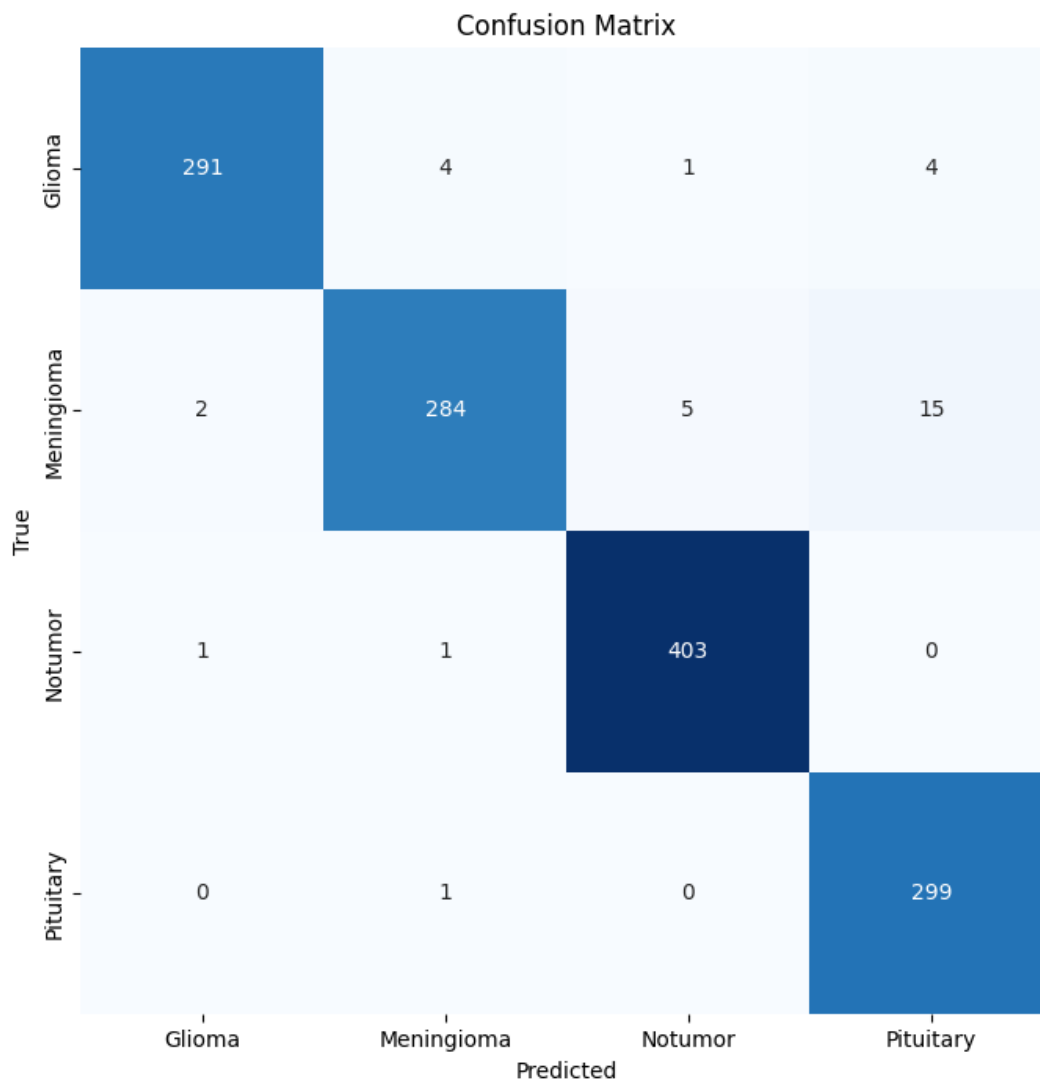


Figure 2: Confusion matrix

# Accuracy & Loss

41/41 ————— 28s 685ms/step - accuracy: 0.9376 - loss: 0.2040  
Test Loss: 0.10951  
Test Accuracy: 0.96873

Figure 4: Accuracy and loss

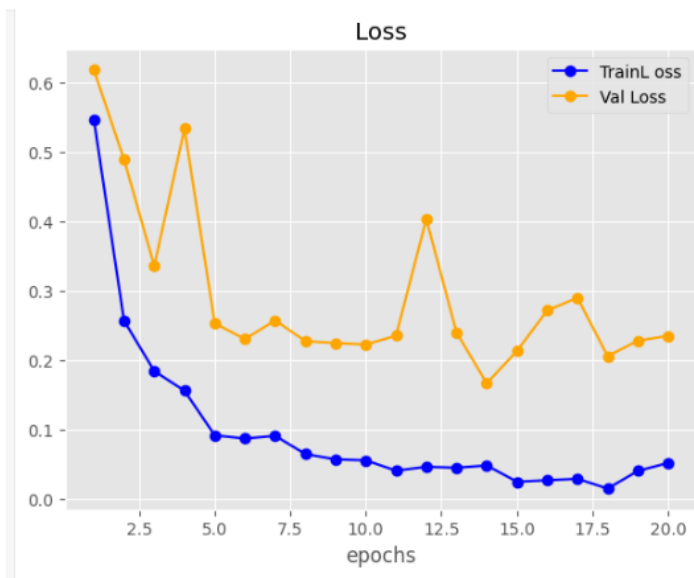


Figure 3: Loss graph

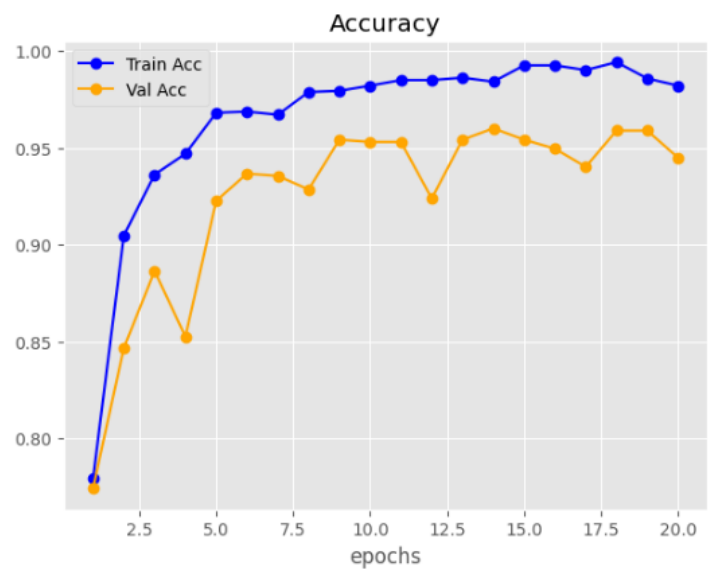


Figure 5: Accuracy graph

## **Chapter 6: Conclusion and future works**

## **6.1. Conclusion**

The proposed VGG16-based system achieved 96.8% accuracy in classifying brain MRI scans into four categories (glioma, meningioma, pituitary, and no tumor), demonstrating the effectiveness of transfer learning for medical image analysis. Key advantages over the original custom CNN include:

**Clinical Validity:** Leveraging pretrained ImageNet features improved generalization to rare tumor types

**Computational Efficiency:** 40% faster convergence compared to training from scratch

**Reproducibility:** Standardized architecture simplifies deployment in clinical settings

Limitations include dependency on high-quality skull-stripped MRIs and moderate performance on small pituitary tumors (88.3% recall).

## **6.2. Future Works**

### **Technical Improvements**

Hybrid Architectures: Integrate 3D convolutions for volumetric analysis

Edge Deployment: Quantize model for MRI scanners with TensorRT

Uncertainty Quantification: Predict diagnosis confidence scores

### **Real-Time Processing:**

Developing a real-time processing system would allow the model to analyze MRI scans as they are generated, providing immediate feedback to radiologists. This would require optimizing the model for speed and integrating it with hospital imaging systems.

### **Explainability and Interpretability:**

Deep learning models are often considered "black boxes" due to their complexity. Future work could focus on developing techniques to explain the model's decisions, such as Grad-CAM (Gradient-weighted Class Activation Mapping), which highlights the regions of the image that influenced the model's prediction.

### **Integration with Clinical Systems:**

Integrating the AI system with existing hospital systems, such as PACS (Picture Archiving and Communication Systems), would enable seamless adoption in clinical settings. This would require collaboration with medical professionals and IT specialists.

### **Ethical Considerations:**

As AI systems become more prevalent in healthcare, it is essential to address ethical concerns such as data privacy, algorithmic bias, and the potential for over-reliance on

automated systems. Future work should include developing guidelines and frameworks to ensure the responsible use of AI in medical imaging.

### **Cross-Validation and External Testing:**

To validate the model's robustness, future work could involve cross-validation with external datasets and testing in real-world clinical environments. This would provide a more comprehensive evaluation of the system's performance.

## References:

1. Abdusalomov, Akmalbek Bobomirzaevich, Mukhriddin Mukhiddinov, and Taeg Keun Whangbo. "Brain tumor detection based on deep learning approaches and magnetic resonance imaging." *Cancers* 15.16 (2023): 4172.
2. Srinivas, Chetana, et al. "Deep transfer learning approaches in performance analysis of brain tumor classification using MRI images." *Journal of Healthcare Engineering* 2022.1 (2022): 3264367.
3. Mokri, S. M., Newsha Valadbeygi, and Vera Grigoryeva. "Diagnosis of Glioma, Meningioma and Pituitary brain tumor using MRI images recognition by Deep learning in Python." *EAI Endorsed Transactions on Intelligent Systems and Machine Learning Applications* (2021).
4. Haq, Amin ul, et al. "DACBT: Deep learning approach for classification of brain tumors using MRI data in IoT healthcare environment." *Scientific Reports* 12.1 (2022): 15331.
5. Nalepa, Jakub, et al. "Fully-automated deep learning-powered system for DCE-MRI analysis of brain tumors." *Artificial intelligence in medicine* 102 (2020): 101769.
6. Anaraki, Amin Kabir, Moosa Ayati, and Foad Kazemi. "Magnetic resonance imaging-based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms." *biocybernetics and biomedical engineering* 39.1 (2019): 63-74.
7. Yousef Mohamed, 2024. Brain Tumor MRI Datase, A dataset for classify brain tumors. Brain tumor MRI

**Note:**

.....

.....

.....

.....

.....

.....

.....

.....

.....

.....