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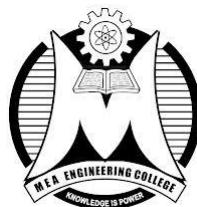
# Enhancing Brain Tumour Diagnosis With Transfer Learning

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*A project report  
submitted in fulfillment of  
the requirements for the award of the degree of  
BACHELOR OF TECHNOLOGY  
in  
Computer Science & Engineering  
from  
APJ ABDUL KALAM KERALA TECHNOLOGICAL  
UNIVERSITY*



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## Certificate

*This is to certify that the Project report entitled “Enhancing Brain Tumour Diagnosis With Transfer Learning” is a bonafide record of the work done by MINHAJ AKAVALAP-PIL (MEA21CS036), MOHAMMED AFLAH (MEA21CS037), MOHAMMED ASEEL (MEA21CS038), MOHAMMED JASIM A. (MEA21CS043) under our supervision and guidance. The report has been submitted in fulfillment of the requirement for award of the Degree of Bachelor of Technology in Computer Science & Engineering from the APJ Abdul Kalam Kerala Technological University for the year 2025.*

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## *Abstract*

Brain tumors present a significant challenge in medical diagnosis due to their heterogeneous nature and complex imaging characteristics. Early and accurate detection is crucial for effective treatment and improved patient outcomes. This project introduces a deep learning-based framework that integrates transfer learning with EfficientNet-B0 and YOLOv8 for precise tumor classification and segmentation. EfficientNet-B0, fine-tuned using transfer learning, categorizes brain tumors into four types: glioma, meningioma, pituitary, and no tumor. Meanwhile, YOLOv8 is employed for high-speed, real-time segmentation, enabling precise localization of tumor regions within MRI scans.

Transfer learning plays a crucial role in enhancing the model's generalization by leveraging pre-trained weights, thereby reducing training time and improving performance on limited medical imaging datasets. The integration of EfficientNet-B0 ensures high classification accuracy, while YOLOv8 facilitates real-time segmentation with minimal computational overhead. Extensive experiments validate the effectiveness of the proposed framework, demonstrating superior accuracy, computational efficiency, and robustness compared to conventional methods.

By automating brain tumor detection and segmentation, this framework addresses the critical need for early diagnosis, reducing the workload on radiologists and medical professionals. The proposed approach enhances diagnostic precision, ensuring timely and effective treatment planning. With its real-time capabilities and high accuracy, the framework has significant potential for clinical implementation, contributing to improved healthcare outcomes and more efficient medical imaging analysis.

# List of Abbreviations

<b>CNN</b>	Convolutional Neural Network
<b>DNN</b>	Deep Neural Networks
<b>CT</b>	Computed Tomography
<b>MRI</b>	Magnetic Resonance Imaging
<b>TL</b>	Transfer Learning
<b>GAN</b>	Generative Adversarial Networks
<b>TP</b>	True Positive
<b>TN</b>	True Negative
<b>FP</b>	False Positive
<b>FN</b>	False Negative
<b>Grad-CAM</b>	Gradient-weighted Class Activation Mapping
<b>PET</b>	Positron Emission Tomography
<b>HIPAA</b>	Health Insurance Portability and Accountability Act
<b>SMOTE</b>	Synthetic Minority Over-sampling Technique

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# CHAPTER 1

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## Introduction

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Brain tumors are serious and life-threatening conditions that require early detection for better treatment outcomes. MRI (Magnetic Resonance Imaging) is a widely used imaging technique to identify brain tumors, but analyzing these images manually is time-consuming, prone to errors, and requires highly trained professionals. To address these challenges, this study uses artificial intelligence (AI) to automate and improve brain tumor detection.

Deep learning, a branch of AI, has made significant advancements in medical imaging. Convolutional Neural Networks (CNNs) have proven highly effective in analyzing complex medical images, outperforming traditional methods. These models can automatically identify patterns in MRI scans, making them valuable tools for diagnosing brain tumors more accurately and efficiently.

This project utilizes EfficientNet-B0 for tumor classification and YOLOv8 for segmentation. EfficientNet-B0 is a CNN known for its high accuracy with fewer parameters, making it computationally efficient. By using transfer learning, the model is trained on MRI scans to classify tumors into gliomas, meningiomas, pituitary tumors, or no tumor. This approach reduces the need for large datasets and improves the model's ability to generalize across different cases.

Accurate segmentation of tumors is equally important for diagnosis and treatment planning. YOLOv8, a cutting-edge object detection model, is used to segment tumor regions in MRI scans. Unlike traditional methods that require multiple steps, YOLOv8 performs detection and segmentation simultaneously, ensuring fast and precise results. This makes it highly suitable for real-time medical applications.

By combining EfficientNet-B0 and YOLOv8, this study provides a comprehensive solution for brain tumor diagnosis. EfficientNet-B0 classifies tumors efficiently, while

YOLOv8 accurately identifies and segments affected regions. This integrated framework enhances the accuracy and speed of diagnosis, supporting medical professionals in making informed treatment decisions.

Data preprocessing is essential for improving model performance. MRI scans undergo steps like normalization, noise reduction, and augmentation to enhance data quality. Augmentation techniques such as rotation, flipping, and contrast adjustment help the model learn better and reduce overfitting, improving overall accuracy.

The trained models are evaluated using key metrics such as accuracy, sensitivity, and specificity. These metrics ensure the reliability of the framework in detecting brain tumors. High accuracy and sensitivity mean better detection rates, while specificity helps in minimizing false positives.

The goal of this project is to create a reliable diagnostic tool that integrates seamlessly into clinical workflows. By automating tumor classification and segmentation, this system can reduce the workload on radiologists, minimize diagnostic errors, and speed up the decision-making process. The AI-powered system acts as a valuable second opinion for medical experts.

This research contributes to the growing field of AI in healthcare, demonstrating how deep learning can improve medical diagnostics. As AI technology advances, its integration into hospitals and clinics will become more common, enhancing patient care and medical decision-making. This study showcases the potential of EfficientNet-B0 and YOLOv8 in transforming brain tumor detection and improving patient outcomes.

In summary, this project combines EfficientNet-B0 for classification and YOLOv8 for segmentation to enhance brain tumor detection. This approach improves diagnostic accuracy and efficiency, making it a practical solution for real-world medical applications. By bridging AI advancements with clinical needs, this research paves the way for better healthcare solutions.

## 1.1 Challenges in Traditional Brain Tumor Detection Methods

- **Time-Consuming and Labor-Intensive :** Manual MRI analysis requires significant expertise, taking hours or days, delaying diagnosis and treatment. This prolonged process can lead to late-stage detection, reducing the chances of successful intervention.

- **Dependence on Expert Radiologists:** Skilled professionals are scarce, and subjective interpretations can lead to inconsistent diagnoses. The increasing demand for radiologists further exacerbates the challenge, making timely diagnosis difficult in high-patient-load settings.
- **Difficulty in Detecting Small or Overlapping Tumors :** Subtle, small, or complex tumors can be missed due to low contrast in MRI scans or overlapping structures. This limitation can result in incorrect classification, affecting treatment plans and patient outcomes.
- **Prone to Human Error :** Variability in radiologist expertise and fatigue can result in misdiagnoses, affecting treatment decisions. Even experienced professionals may struggle with distinguishing between tumor types, leading to diagnostic uncertainty.
- **Limited Automation and Scalability :** Traditional methods lack real-time, automated solutions, making large-scale screenings inefficient. As a result, hospitals and diagnostic centers face challenges in handling increasing medical imaging workloads.

## 1.2 The Role of Transfer Learning

To address these challenges, transfer learning has emerged as a powerful technique in the realm of medical imaging, particularly for brain tumor detection. Transfer learning leverages pre-trained models that have already been trained on large, general datasets—such as ImageNet—and adapts them for specific tasks like detecting brain tumors. This approach offers several advantages:

- **Reduced Data Requirements:** By utilizing a pre-trained model, the need for large amounts of labeled data is significantly diminished. Transfer learning allows practitioners to fine-tune models on smaller datasets, achieving high levels of accuracy without the burden of extensive data collection.
- **Lower Computational Demands:** Since the majority of the model's parameters are pre-trained, transfer learning reduces the computational resources and time required for training. This makes it feasible to implement effective diagnostic models even in resource-constrained environments.
- **Mitigation of Overfitting:** Transfer learning inherently reduces the risk of overfitting by leveraging features learned from diverse datasets. The pre-trained model captures generalized patterns, allowing the fine-tuned model to focus on the specific characteristics of brain tumors without memorizing limited training data.

### 1.3 Transfer Learning in Brain Tumor Detection

Transfer learning involves using a pre-trained CNN model as a starting point, rather than training a model from scratch. CNNs are well-suited for medical imaging tasks because they are designed to process grid-like data, such as images, and can automatically extract relevant features like edges, shapes, and textures. By using a model that has already learned these fundamental features from a large dataset, it is possible to fine-tune the model to detect brain tumors with greater accuracy and efficiency.

Here's how transfer learning typically works for brain tumor detection:

- **Pre-trained Model Selection:** Popular CNN architectures such as VGG16, ResNet, EfficientNetB0, Inception, and MobileNet are often used. These models are initially trained on large datasets like ImageNet, which contain millions of general images across a wide range of categories.
- **Feature Extraction:** The lower layers of the pre-trained model capture general features such as edges and textures. These layers are retained, while the upper layers, which are specific to the original task, are replaced with new layers tailored to the brain tumor detection task.
- **Fine-tuning:** The new model is trained on the brain tumor dataset, but with significantly fewer parameters to adjust, as most of the network's weights are already optimized for feature extraction. This fine-tuning process allows the model to learn domain-specific features related to brain tumors.

### 1.4 Benefits of Transfer Learning for Brain Tumor Detection

- **Reduced Training Time:** Transfer learning significantly decreases the time required to train models for specific medical imaging tasks. Since a substantial portion of the model's parameters are already pre-trained on large datasets, only the final layers need fine-tuning. This efficiency allows for faster deployment in clinical settings.
- **Improved Accuracy with Less Data:** By leveraging knowledge from pre-trained models, transfer learning enables high accuracy even when the training dataset is limited. This is particularly beneficial in medical applications, where acquiring large, annotated datasets can be challenging and time-consuming.
- **Efficient Use of Computational Resources:** Transfer learning minimizes the need for extensive computational resources typically required for training deep learning

models from scratch. This makes it feasible to implement high-performing models on standard hardware, broadening access to advanced diagnostic tools in healthcare facilities with limited resources.

- **Overcoming Data Scarcity:** Transfer learning is especially advantageous in situations where large, labeled datasets are unavailable. It allows medical professionals to build effective deep learning models, facilitating accurate tumor detection and classification without the need for vast amounts of training data. This capability is crucial in the medical field, where data can be limited and costly to obtain.

## 1.5 What Is Exactly Transferred From Pre-trained Model

### 1. Weights and Biases

- **Pre-trained Parameters:** The model's weights and biases, which have been optimized during training on a large dataset (e.g., ImageNet), are transferred. These parameters encapsulate the learned features and patterns relevant to image recognition tasks.

### 2. Feature Extraction Layers

- **Hierarchical Feature Representation:** EfficientNet-B0 consists of multiple layers, each designed to learn different levels of abstraction. Early layers capture low-level features (e.g., edges, textures), while deeper layers capture high-level features (e.g., shapes, object parts). When transferred, these layers can be utilized for feature extraction in the target task, such as brain tumor detection.

### 3. Knowledge of Data Distribution

- **Generalization to Similar Tasks:** The model's understanding of visual data patterns and distributions acquired during training helps improve performance on the target dataset. This is especially useful when the target dataset is limited in size or diversity.

### 4. Model Architecture

- **Network Structure:** The architecture of EfficientNet-B0 itself—comprising its convolutional blocks, activation functions, and pooling layers—can be beneficial. This design is optimized for efficiency and accuracy, providing a solid foundation for subsequent fine-tuning.

### 5. Training Techniques

- **Optimization Strategies:** Techniques used during the training of EfficientNet-B0, such as specific learning rates, batch normalization, and dropout, can be adapted or reused when fine-tuning the model on the target dataset. This aids in stabilizing the training process and improving convergence.

## 6. Regularization Effects

- **Reduced Overfitting Risk:** The pre-trained weights serve as a form of regularization, helping the model generalize better and reducing the likelihood of overfitting, particularly when the target dataset is small.

## 1.6 Proposed AI-Powered Framework for Brain Tumor Diagnosis

This study presents an AI-based framework that integrates transfer learning with EfficientNet-B0 for tumor classification and YOLOv8 for real-time tumor segmentation. The key components of the proposed framework include:

### 1.6.1 Transfer Learning with EfficientNet-B0

EfficientNet-B0, a highly optimized CNN architecture, is used in this study to classify brain tumors into four categories: glioma, meningioma, pituitary, and no tumor. Transfer learning is applied by utilizing pre-trained weights from large-scale image datasets and fine-tuning the model on MRI scans. This approach enhances classification accuracy while reducing computational complexity and training time.

#### Why EfficientNet-B0 Over Other Versions?

EfficientNet comes in multiple versions (B0 to B7), with higher versions offering increased model depth, width, and resolution. However, EfficientNet-B0 is selected for this study due to the following reasons:

- **Computational Efficiency:** EfficientNet-B0 has fewer parameters compared to higher versions, making it more suitable for real-time and resource-constrained applications.
- **Comparable Accuracy:** Studies have shown that EfficientNet-B0 achieves high classification accuracy with minimal computational overhead, making it an optimal choice for medical imaging tasks.
- **Scalability:** EfficientNet-B0 can be fine-tuned effectively on small medical datasets, whereas higher versions require significantly more data and computational power.
- **Faster Training and Inference:** The lightweight nature of EfficientNet-B0 allows for quicker model training and inference times, ensuring efficient real-world deployment.

### 1.6.2 YOLOv8 for Real-Time Tumor Segmentation

YOLOv8, a state-of-the-art object detection model, is employed for high-speed, real-time tumor segmentation. This model enables precise localization of tumor regions within MRI scans, facilitating improved visualization and aiding radiologists in making informed decisions. YOLOv8's fast inference speed and robust detection capabilities make it an ideal choice for real-world clinical applications.

#### Why YOLOv8 Over Other Versions?

YOLO (You Only Look Once) has evolved through multiple iterations, with YOLOv8 being the latest and most advanced version. The decision to use YOLOv8 is based on the following factors:

- **Improved Detection Accuracy :** YOLOv8 incorporates advanced architectural optimizations, leading to better object detection performance compared to earlier versions (YOLOv3, YOLOv4, and YOLOv5).
- **Faster Inference Speed :** YOLOv8 is designed for real-time applications, offering high-speed segmentation without compromising accuracy.
- **Better Feature Extraction :** YOLOv8 integrates enhanced backbone networks and attention mechanisms, improving feature extraction from complex medical images.
- **Optimized Model Efficiency :** Compared to YOLOv7, YOLOv8 maintains high accuracy while being more computationally efficient, making it well-suited for medical imaging tasks where real-time segmentation is critical.

# CHAPTER 2

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## Background Information

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Brain tumors can be classified into various types, including gliomas, meningiomas, and pituitary tumors, each presenting unique challenges in diagnosis and treatment. The heterogeneity of brain tumors makes accurate classification essential for determining appropriate treatment strategies, such as surgery, radiation, or chemotherapy. Traditional methods rely heavily on radiologists' expertise, but due to the complex nature of MRI scans, misinterpretations and diagnostic delays can occur, impacting patient outcomes. This section explores the fundamentals of brain tumors, MRI image acquisition, challenges in manual diagnosis, and the role of AI-based approaches, particularly EfficientNet-B0 for classification and YOLOv8 for real-time segmentation, in enhancing brain tumor detection.

### 2.1 Brain Tumors: An Overview

Brain tumors are abnormal masses of tissue resulting from uncontrolled cell growth within the brain. They are categorized as:

#### 2.1.1 Benign Tumors

Benign brain tumors are non-cancerous and typically slow-growing. Although they do not invade nearby tissues, their presence within the enclosed skull can still lead to significant neurological complications. Some common benign tumors include:

- (i) **Meningioma:** Arising from the meninges (protective membranes covering the brain and spinal cord), meningiomas are among the most common primary brain tumors. Although they are usually benign, their location can cause compression of brain structures.

**(ii) Pituitary Tumors:** Originating in the pituitary gland, these tumors can affect hormone production, leading to endocrine disorders such as Cushing's disease or acromegaly.

### 2.1.2 Malignant Tumors

Malignant brain tumors are cancerous, aggressive, and can rapidly invade surrounding brain tissue. These tumors often require immediate medical intervention. Examples include:

- (i) Glioblastoma Multiforme (GBM):** One of the most aggressive forms of brain cancer, GBM has a poor prognosis due to its rapid growth and resistance to conventional therapies.
- (ii) Astrocytoma:** A type of glioma originating from astrocytes (star-shaped glial cells). Low-grade astrocytomas may progress to more aggressive forms over time.

### 2.1.3 Primary Tumors

Primary brain tumors originate within the brain itself and do not spread from other parts of the body. These tumors can be either benign or malignant. Some examples include:

- (i) Gliomas:** Tumors that arise from glial cells, which support and protect neurons. Gliomas encompass astrocytomas, oligodendrogiomas, and ependymomas.
- (ii) Ependymomas:** These tumors develop in the ependymal cells lining the ventricles of the brain and spinal cord, often affecting cerebrospinal fluid dynamics.

### 2.1.4 Secondary (Metastatic) Tumors

Unlike primary tumors, metastatic brain tumors originate from cancers elsewhere in the body and spread to the brain. Common sources of brain metastases include:

- (i) Lung cancer:** The most frequent source of brain metastases.
- (ii) Breast cancer:** Can spread to the brain, especially in later stages.
- (iii) Melanoma, kidney, and colon cancer:** These cancers also have a higher likelihood of metastasizing to the brain.

Early detection is crucial, as tumors can disrupt neurological functions, motor skills, and cognitive abilities. MRI scanning remains the gold standard for brain tumor diagnosis, but manual interpretation has limitations, necessitating AI-powered solutions.

## 2.2 Collection and Processing of MRI Images for Brain Tumor Detection

### 2.2.1 MRI Image Acquisition

Magnetic Resonance Imaging (MRI) uses a strong magnetic field and radio waves to create detailed images of brain structures. Magnetic Resonance Imaging (MRI) is a non-invasive medical imaging technique widely used for diagnosing brain tumors due to its high-resolution soft tissue contrast. Unlike X-ray or CT scans, MRI does not use ionizing radiation; instead, it relies on strong magnetic fields and radio waves to generate detailed images of the brain. MRI is particularly effective in detecting tumor size, location, and type, making it an essential tool for neurosurgeons and radiologists. It provides superior soft tissue contrast compared to other imaging techniques like Computed Tomography (CT). The MRI acquisition process includes the following steps:

- (i) **Patient Preparation :** The patient is positioned inside the MRI scanner, ensuring minimal movement. Metal objects (jewelry, implants) are removed due to the magnetic field. A contrast agent (e.g., gadolinium) may be injected to enhance tumor visibility.
- (ii) **MRI Scan Sequences :** MRI generates images in different sequences, each highlighting specific tissue properties:
  - **T1-weighted MRI:** Provides high-resolution anatomical details.
  - **T2-weighted MRI:** Highlights water content, making tumors more visible.
  - **FLAIR (Fluid-Attenuated Inversion Recovery):** Suppresses normal fluid signals, enhancing tumor detection.

### 2.2.2 Preprocessing of MRI Images

Once acquired, MRI images undergo preprocessing before analysis to improve their quality and suitability for AI-based classification and segmentation:

- **Noise Reduction:** Eliminates unwanted artifacts for clearer images.
- **Intensity Normalization:** Standardizes brightness levels across different scans.
- **Segmentation:** Extracts relevant brain regions, distinguishing tumors from normal tissues.

These preprocessed images are then used for manual diagnosis by radiologists or further analyzed using Deep Learning models.

### 2.2.3 Functional MRI (fMRI) and Image Extraction

- **Introduction to fMRI**

Functional MRI (fMRI) is a specialized imaging technique that measures brain activity by detecting changes in blood oxygenation levels. Unlike conventional MRI, which provides structural details, fMRI captures real-time functional responses associated with brain activity.

- **Extracting Structural MRI Images from fMRI**

For brain tumor diagnosis, structural MRI images are extracted from fMRI datasets using the following techniques:

- (i) Temporal Averaging: Averages multiple fMRI time points to reconstruct a static MRI scan.
- (ii) Segmentation Algorithms: Separates functional data from anatomical features.
- (iii) Registration Techniques: Aligns fMRI data with standard MRI scans for precise localization of tumors.

By extracting structural information from fMRI, AI models can enhance tumor detection and assess functional impairments caused by tumor growth.

## 2.3 Role of AI in Medical Imaging

Artificial Intelligence (AI) has transformed medical imaging by enhancing the speed, accuracy, and efficiency of disease diagnosis. Traditional diagnostic methods rely on radiologists manually interpreting medical images, a process that can be time-consuming, prone to human error, and affected by inter-observer variability. AI-driven solutions, particularly deep learning models, have introduced automated systems that assist in detection, classification, and segmentation of abnormalities in medical images, leading to faster and more reliable diagnoses.

### 2.3.1 Deep Learning and Convolutional Neural Networks (CNNs)

Deep Learning, especially Convolutional Neural Networks (CNNs), has revolutionized medical imaging by automating feature extraction and enabling efficient disease detection. Unlike conventional machine learning methods that require handcrafted feature engineering, CNNs learn hierarchical features from raw image data, capturing edges, textures, patterns, and high-level structures that are critical for detecting anomalies such as brain tumors.

CNNs consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers, which work together to analyze complex medical images. The convolutional layers extract important features, while the pooling layers reduce dimensionality, making computations more efficient. By passing MRI scans through multiple layers, CNNs can learn to differentiate between normal and abnormal tissues, allowing precise tumor classification and segmentation.

In brain tumor detection, CNN-based architectures such as EfficientNet, ResNet, and VGG have demonstrated remarkable accuracy. EfficientNet-B0, in particular, is widely used due to its lightweight architecture and high efficiency, making it suitable for real-time medical applications. When trained on large medical datasets, CNN models can generalize well, leading to improved diagnostic accuracy and consistency compared to human interpretation alone.

### 2.3.2 Transfer Learning in Medical AI

One of the biggest challenges in medical imaging is the limited availability of labeled datasets, as acquiring and annotating medical images requires expert radiologists and significant resources. Transfer learning addresses this issue by allowing AI models to leverage pre-trained weights from general-purpose datasets (such as ImageNet) and fine-tune them for medical applications like brain tumor detection.

Pre-trained CNN models, such as EfficientNet-B0, ResNet, and Inception, have been trained on millions of images from diverse domains. While these datasets may not contain medical images, the learned features (such as edges, shapes, and textures) are transferable to medical imaging tasks. By fine-tuning these models on MRI datasets, transfer learning significantly reduces training time, computational costs, and the risk of overfitting, while still achieving high accuracy.

In the context of brain tumor classification, transfer learning enables CNN models to efficiently distinguish between different tumor types—such as glioma, meningioma, and pituitary tumors—with minimal labeled data. This approach has proven highly effective in low-resource settings, where acquiring large medical datasets is challenging. Additionally, transfer learning makes it possible to deploy AI-driven diagnostic tools in real-world clinical environments with minimal retraining, improving accessibility to AI-powered healthcare.

## 2.4 EfficientNet-B0 for Brain Tumor Classification

### 2.4.1 Overview of EfficientNet

EfficientNet is a state-of-the-art Convolutional Neural Network (CNN) architecture designed to optimize both accuracy and computational efficiency. Unlike traditional deep learning models, which often increase accuracy by simply adding more layers or parameters, EfficientNet uses a novel technique called compound scaling to systematically balance the depth, width, and resolution of the network. This ensures that the model improves performance without significantly increasing computational costs.

The compound scaling method involves:

- Scaling depth – Increasing the number of layers to improve feature extraction.
- Scaling width – Expanding the number of channels in each layer to capture richer representations.
- Scaling resolution – Enlarging input image size to retain more fine-grained details. By scaling these three factors uniformly, EfficientNet achieves a better trade-off between accuracy and efficiency compared to conventional CNN architectures like ResNet, VGG, and DenseNet. This makes it particularly suitable for medical imaging tasks, where high accuracy is required without excessive computational overhead.

### 2.4.2 Why EfficientNet-B0?

EfficientNet-B0 is the smallest and most lightweight variant of the EfficientNet family, making it an ideal choice for brain tumor classification in medical imaging. It is designed to offer high performance with minimal computational cost, making it suitable for real-time and resource-constrained applications. Some key advantages of using EfficientNet-B0 for brain tumor classification include:

- (i) **Higher accuracy compared to traditional CNNs** – EfficientNet-B0 consistently outperforms architectures like ResNet, VGG, and Inception in terms of classification accuracy, making it a reliable choice for detecting different brain tumor types (glioma, meningioma, and pituitary tumors).
- (ii) **Fewer parameters and reduced computational complexity** – While deeper networks like ResNet-50 or VGG-19 require millions of parameters, EfficientNet-B0 achieves similar or better performance with fewer parameters, leading to faster inference times and lower memory usage.

**(iii) Pre-trained on ImageNet and fine-tuned for MRI-based tumor classification** – Since medical datasets are often limited, EfficientNet-B0 can be pre-trained on large-scale datasets (such as ImageNet) and then fine-tuned on brain MRI images. This transfer learning approach significantly improves classification accuracy while requiring less training data.

**(iv) Improved feature extraction** – The model's advanced convolutional layers and optimized architecture allow it to effectively capture complex patterns and subtle variations in brain tumor images, enhancing diagnostic precision.

**(v) Better generalization** – EfficientNet-B0 is designed to reduce overfitting, making it more robust when applied to different MRI datasets and real-world medical scenarios.

By leveraging EfficientNet-B0 for brain tumor classification, AI-driven diagnostic systems can achieve faster, more accurate, and computationally efficient tumor detection, ultimately aiding radiologists in early diagnosis and treatment planning.

## 2.5 YOLOv8 for Brain Tumor Segmentation

### 2.5.1 Introduction to YOLO (You Only Look Once)

YOLO (You Only Look Once) is a real-time object detection algorithm that processes an entire image in a single forward pass, making it significantly faster than traditional multi-stage detection models like R-CNN. By dividing an image into a grid and predicting bounding boxes and class probabilities simultaneously, YOLO ensures high-speed detection while maintaining accuracy.

With its advancements over earlier versions, YOLOv8 has become highly efficient for brain tumor segmentation in MRI scans, offering real-time processing, improved feature extraction, and precise tumor localization. Its ability to detect and classify tumors quickly makes it an ideal tool for AI-driven medical image analysis.

### 2.5.2 Advancements in YOLOv8

- 1. Enhanced Segmentation Accuracy** - YOLOv8 improves tumor boundary detection by integrating advanced convolutional layers and attention mechanisms, reducing segmentation errors and ensuring better differentiation between tumor and healthy tissue.

- 2. Faster Processing Speeds** - With optimized deep learning architectures and GPU acceleration, YOLOv8 enables real-time tumor analysis, reducing diagnosis time and assisting radiologists in quicker decision-making.
- 3. Better Adaptability to MRI Scans** - YOLOv8 is designed to handle varied MRI modalities (T1, T2, FLAIR, contrast-enhanced), ensuring robustness across different imaging conditions and improving diagnostic consistency.
- 4. Improved Feature Extraction** - With deeper convolutional layers and spatial pyramid pooling, YOLOv8 captures intricate tumor details, aiding in the detection of small or low-contrast tumors that might be missed by conventional methods.
- 5. Optimized Tumor Localization** - YOLOv8 employs refined bounding box regression techniques, reducing false positives and false negatives, leading to more precise tumor detection and segmentation.
- 6. Effective Post-Processing** - Techniques like Non-Maximum Suppression (NMS) and Soft-NMS refine final detections, removing redundant bounding boxes and improving overall segmentation clarity.

YOLOv8's speed, accuracy, and adaptability make it a powerful tool for brain tumor detection and segmentation in MRI scans. By leveraging deep learning advancements, it enhances early diagnosis, treatment planning, and patient outcomes, reinforcing AI's growing role in medical imaging and automated diagnostics.

# CHAPTER 3

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## Literature Review

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### 3.1 A Deep Analysis of Brain Tumor Detection from MR Images Using Deep Learning Networks [1]

Creating machines that behave and work in a way similar to humans is the objective of artificial intelligence (AI). In addition to pattern recognition, planning, and problem-solving, computer activities with artificial intelligence include other activities. A group of algorithms called “deep learning” is used in machine learning. With the aid of magnetic resonance imaging (MRI), deep learning is utilized to create models for the detection and categorization of brain tumors. This allows for the quick and simple identification of brain tumors.

Brain disorders are mostly the result of aberrant brain cell proliferation, which can harm the structure of the brain and ultimately result in malignant brain cancer. The early identification of brain tumors and the subsequent appropriate treatment may lower the death rate. In this study, we suggest a convolutional neural network (CNN) architecture for the efficient identification of brain tumors using MR images. This paper also discusses various models such as ResNet-50, VGG16, and Inception V3 and conducts a comparison between the proposed architecture and these models.

To analyze the performance of the models, we considered different metrics such as the accuracy, recall, loss, and area under the curve (AUC). As a result of analyzing different models with our proposed model using these metrics, we concluded that the proposed model performed better than the others. Using a dataset of 3264 MR images, we found that the CNN model had an accuracy of 93.3%, an AUC of 98.43%, a recall of 91.19%, and a loss of 0.25. We may infer that the proposed model is reliable for the early detection of a variety of brain tumors after comparing it to the other models.

### 3.1.1 Methodology

- **Data Acquisition:** Gather a dataset of MRI images from publicly available databases or clinical sources, ensuring a balance between normal and tumor-affected images. Preprocess the images (resizing, normalization) to prepare them for model input.
- **Data Preprocessing:** Apply techniques such as histogram equalization to enhance image contrast. Use data augmentation (rotation, flipping, zooming) to increase dataset diversity and improve model robustness.
- **Model Selection:** Choose a deep learning architecture, commonly Convolutional Neural Networks (CNNs) due to their effectiveness in image classification tasks. Consider using pre-trained models (e.g., VGG16, ResNet, Inception) to leverage transfer learning.
- **Training the Model:** Split the dataset into training, validation, and test sets. Train the model using the training set, employing techniques such as batch normalization, dropout, and early stopping to prevent overfitting. Optimize model hyperparameters using techniques like grid search or random search.
- **Model Evaluation:** Evaluate the model's performance using metrics such as accuracy, precision, recall, F1 score, and area under the ROC curve (AUC). Use confusion matrices to analyze the classification results in detail.
- **Post-Processing:** Implement techniques to refine predictions, such as thresholding to classify tumor presence. Visualize model predictions on sample images to interpret the results and assess model performance qualitatively.
- **Deployment:** Prepare the trained model for deployment in a clinical setting, ensuring it meets regulatory standards for medical devices. Create a user-friendly interface for clinicians to input images and receive predictions.

### 3.1.2 Merits

- **High Accuracy:** Deep learning models, particularly CNNs, have shown high accuracy in image classification tasks.  
Automation: Reduces the burden on radiologists by automating tumor detection processes.
- **Consistency:** Provides consistent results that can help standardize diagnosis and reduce human error.
- **Scalability:** Can be scaled to analyze large datasets quickly, facilitating large-scale studies or implementations in clinical practice.

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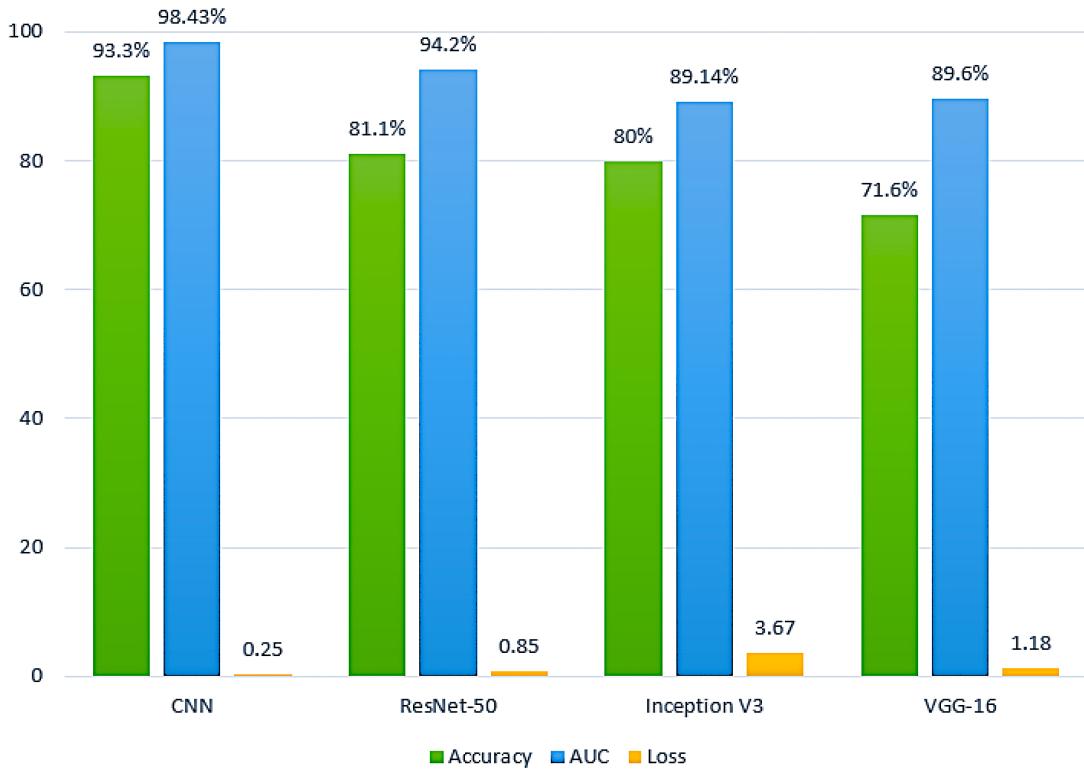


FIGURE 3.1: Performance analysis of the proposed model in terms of the accuracy, AUC, and loss.

### 3.1.3 Demerits

- **Data Dependency:** Performance heavily relies on the quality and quantity of the training data. Insufficient or biased datasets can lead to poor generalization.
- **Interpretability:** Deep learning models are often seen as "black boxes," making it difficult to interpret how decisions are made.
- **Computational Cost:** Training deep learning models can require significant computational resources and time, particularly with large datasets.
- **Overfitting Risk:** If not properly managed, models may overfit to the training data, leading to poor performance on unseen data.

### 3.2 Brain Tumor Detection and Classification Using Intelligence Techniques: An Overview [2]

A tumor is carried on by rapid and uncontrolled cell growth in the brain. If it is not treated in the initial phases, it could prove fatal. Despite numerous significant efforts and encouraging outcomes, accurate segmentation and classification continue to be a challenge. Detection of brain tumors is significantly complicated by the distinctions in tumor position, structure, and proportions. The main disinterest of this study stays to offer investigators, comprehensive literature on Magnetic Resonance (MR) imaging's ability to identify brain tumors.

Using computational intelligence and statistical image processing techniques, this research paper proposed several ways to detect brain cancer and tumors. This study also shows an assessment matrix for a specific system using particular systems and dataset types. This paper also explains the morphology of brain tumors, accessible data sets, augmentation methods, component extraction, and categorization among Deep Learning (DL), Transfer Learning (TL), and Machine Learning (ML) models. Finally, our study compiles all relevant material for the identification of understanding tumors, including their benefits, drawbacks, advancements, and upcoming trends.

Brain tumors represent a significant health challenge, necessitating timely and accurate diagnosis for effective treatment. This overview explores various intelligent techniques employed for the detection and classification of brain tumors using medical imaging, particularly Magnetic Resonance Imaging (MRI). We analyze the evolution of traditional methods, such as image processing and machine learning algorithms, to contemporary approaches that leverage deep learning and artificial intelligence.

#### 3.2.1 Methodology

- **Data Collection:** Gather MRI images from medical databases, ensuring diverse representation of tumor types and stages. Utilize preprocessing techniques to enhance image quality, such as normalization, resizing, and noise reduction.
- **Image Processing:** Apply segmentation techniques to isolate tumor regions from surrounding brain tissue. Methods can include thresholding, region growing, or advanced techniques like U-Net.
- **Feature Extraction:** Extract relevant features from segmented images using traditional methods (e.g., texture, shape) or advanced techniques like deep learning (CNNs) that automatically learn features.

- **Model Selection:** Implement various intelligent techniques, including:  
Machine Learning: Support Vector Machines (SVM), Random Forests, etc.  
Deep Learning: Convolutional Neural Networks (CNNs), transfer learning models (e.g., VGG, ResNet).
- **Model Training and Evaluation:** Split the dataset into training, validation, and test sets. Train models using appropriate loss functions and optimizers. Evaluate performance using metrics like accuracy, precision, recall, F1 score, and AUC-ROC.
- **Post-Processing:** Utilize techniques to enhance classification results, such as thresholding or ensemble methods. Visualize and interpret model predictions to provide insights into decision-making processes.
- **Deployment:** Develop user interfaces or software tools for clinicians, ensuring that models can be integrated into existing workflows.

### 3.2.2 Merits

- **Improved Accuracy:** Intelligent techniques, especially deep learning, often achieve higher diagnostic accuracy compared to traditional methods.
- **Automation:** These methods reduce the workload for radiologists and streamline the diagnostic process.
- **Early Detection:** Enhanced sensitivity allows for earlier identification of tumors, potentially improving patient outcomes.
- **Scalability:** Once trained, these models can analyze large volumes of images quickly, facilitating widespread screening.

### 3.2.3 Demerits

- **Data Limitations:** The performance of models heavily depends on the availability of large, annotated datasets; scarcity or bias can lead to poor generalization.
- **Interpretability Issues:** Deep learning models are often criticized for being black boxes, making it challenging to interpret how decisions are made.
- **Resource Intensive:** Training sophisticated models can be computationally expensive and time-consuming, requiring specialized hardware.
- **Risk of Overfitting:** If models are not properly validated, they may memorize training data rather than generalizing well to unseen cases.

### 3.3 Brain Tumor Identification and Classification of MRI images using deep learning techniques [3]

The detection, segmentation, and extraction from Magnetic Resonance Imaging (MRI) images of contaminated tumor areas are significant concerns; however, a repetitive and extensive task executed by radiologists or clinical experts relies on their expertise. Image processing concepts can imagine the various anatomical structure of the human organ. Detection of human brain abnormal structures by basic imaging techniques is challenging. In this paper, a Fully Automatic Heterogeneous Segmentation using Support Vector Machine (FAHS-SVM) has been proposed for brain tumor segmentation based on deep learning techniques.

The present work proposes the separation of the whole cerebral venous system into MRI imaging with the addition of a new, fully automatic algorithm based on structural, morphological, and relaxometry details. The segmenting function is distinguished by a high level of uniformity between anatomy and the neighboring brain tissue. ELM is a type of learning algorithm consisting of one or more layers of hidden nodes. Such networks are used in various areas, including regression and classification. In brain MRI images, the probabilistic neural network classification system has been utilized for training and checking the accuracy of tumor detection in images. The numerical results show almost 98.51% accuracy in detecting abnormal and normal tissue from brain Magnetic Resonance images that demonstrate the efficiency of the system suggested.

This paper presents a Fully Automatic Heterogeneous Segmentation using Support Vector Machine (FAHS-SVM) for brain tumor identification and segmentation. The accuracy of our automated approach is similar to the values for manual segmentation inter-observer variability. To identify tumor regions by combining intrinsic image structure hierarchy and statistical classification information. The tumor areas described are spatially small and consistent concerning image content and provide an appropriate and robust guide for the consequent segmentation. The proposed method can achieve promising tumor segmentation in conjunction with a semi-supervised approach under a local and globalized accuracy system, as is shown by experiments focused on multi-parametric Magnetic Resonance images.

#### 3.3.1 Methodology

- **Data Acquisition:** Collect a dataset of MRI images from publicly available sources (e.g., The Cancer Imaging Archive, medical institutions). Ensure a balanced

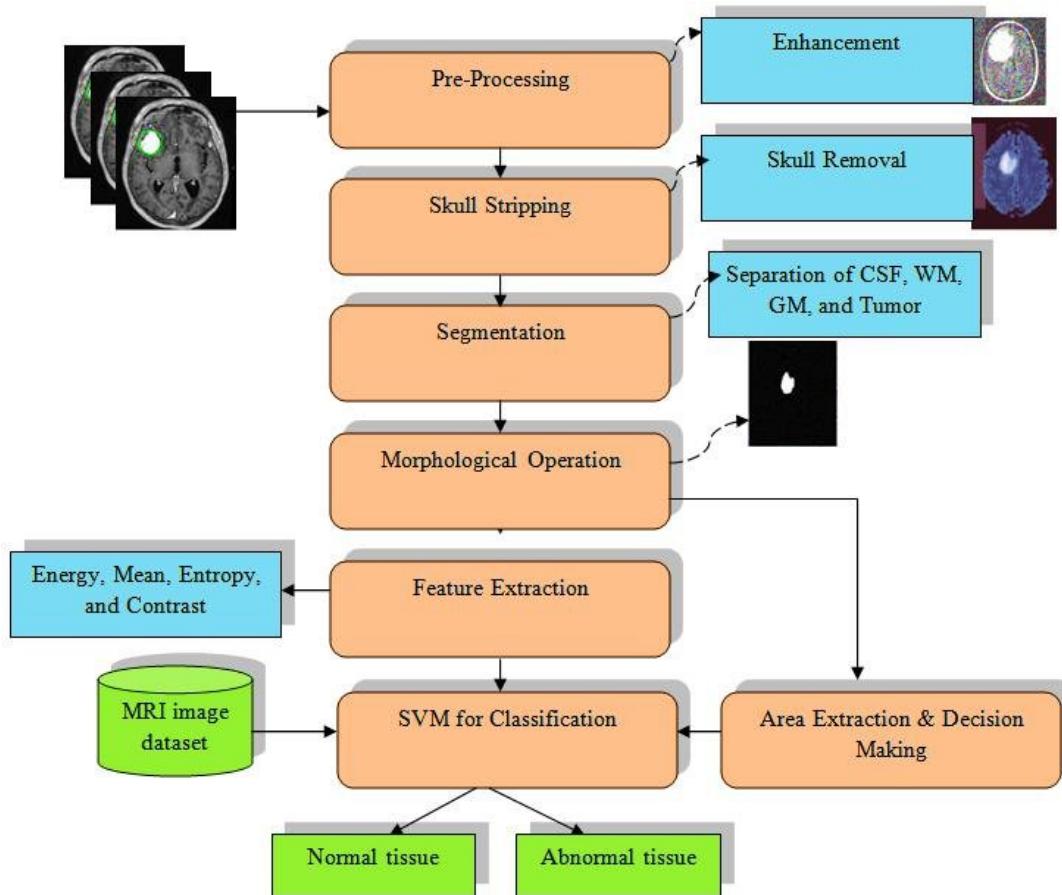


FIGURE 3.2: The proposed FAHS-SVM method architecture i) Pre-Processing

representation of different tumor types (e.g., glioma, meningioma, pituitary tumor) and normal cases.

- **Data Preprocessing:**

- Normalization: Scale pixel values to a range (e.g., 0 to 1) to improve convergence during training.
- Resizing: Resize images to a uniform dimension (e.g., 224x224 pixels) for model input.
- Augmentation: Apply techniques such as rotation, flipping, zooming, and shifting to enhance dataset diversity and reduce overfitting.
- Segmentation (Optional): Utilize segmentation techniques (e.g., U-Net or thresholding) to isolate tumor regions from the surrounding tissue if needed.
- **Model Selection:** Choose a suitable deep learning architecture, primarily Convolutional Neural Networks (CNNs). Consider using transfer learning with pre-trained models (e.g., VGG16, ResNet, Inception) to leverage learned features from large datasets.

- **Training the Model:** Split the dataset into training (70%) and testing (30%) sets. Use categorical cross-entropy as the loss function for multi-class classification. Employ an optimizer like Adam to update model weights. Implement techniques such as dropout and batch normalization to prevent overfitting.
- **Model Evaluation:** Evaluate the model's performance using metrics such as accuracy, precision, recall, F1-score, and the area under the ROC curve (AUC-ROC). Use confusion matrices to visualize the classification results and assess model performance across different tumor types.
- **Post-Processing:** Refine model predictions using thresholding techniques. Visualize predictions on sample images to provide qualitative insights into model performance.
- **Deployment:** Prepare the trained model for clinical use, ensuring compliance with medical device regulations. Develop a user-friendly interface for clinicians to input MRI images and obtain predictions.

### 3.3.2 Merits

- **High Accuracy:** Deep learning models, particularly CNNs, often outperform traditional methods in accurately detecting and classifying brain tumors.
- **Automation:** These techniques reduce the workload for radiologists, enabling faster diagnosis and treatment decisions.
- **Robustness:** Deep learning can handle variability in image quality and characteristics, making it effective across diverse datasets.
- **Feature Learning:** CNNs automatically learn relevant features from data, minimizing the need for manual feature extraction.

### 3.3.3 Demerits

- **Data Dependency:** The effectiveness of deep learning models relies heavily on the availability of large, high-quality, and annotated datasets.
- **Interpretability Issues:** Deep learning models are often viewed as "black boxes," making it difficult for clinicians to understand how decisions are made.
- **Computational Resources:** Training sophisticated models requires substantial computational power, time, and memory, often necessitating specialized hardware (e.g., GPUs).
- **Overfitting Risk:** Without careful tuning and validation, models may overfit to the training data, leading to poor generalization on unseen cases.

### 3.4 Brain Tumor Detection Based on Deep Learning Approaches and Magnetic Resonance Imaging [4]

The rapid development of abnormal brain cells that characterizes a brain tumor is a major health risk for adults since it can cause severe impairment of organ function and even death. These tumors come in a wide variety of sizes, textures, and locations. When trying to locate cancerous tumors, magnetic resonance imaging (MRI) is a crucial tool. However, detecting brain tumors manually is a difficult and time-consuming activity that might lead to inaccuracies.

In order to solve this, we provide a refined You Only Look Once version 7 (YOLOv7) model for the accurate detection of meningioma, glioma, and pituitary gland tumors within an improved detection of brain tumors system. The visual representation of the MRI scans is enhanced by the use of image enhancement methods that apply different filters to the original pictures. To further improve the training of our proposed model, we apply data augmentation techniques to the openly accessible brain tumor dataset. The curated data include a wide variety of cases, such as 2548 images of gliomas, 2658 images of pituitary, 2582 images of meningioma, and 2500 images of non-tumors. We included the Convolutional Block Attention Module (CBAM) attention mechanism into YOLOv7 to further enhance its feature extraction capabilities, allowing for better emphasis on salient regions linked with brain malignancies.

To further improve the model's sensitivity, we have added a Spatial Pyramid Pooling Fast+ (SPPF+) layer to the network's core infrastructure. YOLOv7 now includes decoupled heads, which allow it to efficiently glean useful insights from a wide variety of data. In addition, a Bi-directional Feature Pyramid Network (BiFPN) is used to speed up multi-scale feature fusion and to better collect features associated with tumors. The outcomes verify the efficiency of our suggested method, which achieves a higher overall accuracy in tumor detection than previous state-of-the-art models. As a result, this framework has a lot of potential as a helpful decision-making tool for experts in the field of diagnosing brain tumors.

To reduce global death rates, diagnosis of brain cancers is essential. Brain tumors can be difficult to identify because of their complex architecture, size variability, and unusual forms. In our research, we used a large collection of MRI scans of brain tumors to overcome this obstacle. We showed that a state-of-the-art YOLOv7 model could be improved by transfer learning and fine tuning in order to detect gliomas, meningioma, and pituitary brain tumors in MRI data. Our suggested CNN model demonstrates the substantial influence of deep learning models in tumor identification and demonstrates

how these models have changed this field. Using a huge collection of MRI images, we found some encouraging findings in the diagnosis of brain cancers. We used a wide range of performance measures to measure the effectiveness of our deep learning models.

When compared to standard techniques of categorization, the proposed technology not only detects the existence of brain tumors, but also pinpoints their precise location within the MRI images. This localization allows for fine-grained categorization without laborious human interpretation. The proposed solution, in contrast to segmentation techniques, uses a little amount of storage space and has a low computational cost, making it portable across a variety of systems. Not only did the suggested approach achieve better accuracy than prior efforts using bounding box detection techniques, it also outperformed those techniques when applied to meningioma, glioma, and pituitary brain cancers. The results were improved, and the problem was tackled with the help of picture data augmentation, even though the dataset was relatively small. Using the available data, we obtained an accuracy of 99.5% in our analysis. The proposed method for detecting brain cancers in medical images has achieved this accuracy.

### 3.4.1 Methodology

- **Data Collection:** Acquire a dataset of MRI images containing brain tumors. Sources may include medical databases or clinical studies. Ensure the dataset is annotated with bounding boxes and labels for different tumor types.
- **Data Preprocessing:**
  - Normalization: Normalize pixel values to a range suitable for model input.
  - Resizing: Resize images to the required input size for YOLOv7 (e.g., 640x640 pixels).
  - Augmentation: Apply data augmentation techniques such as rotation, scaling, and flipping to improve model robustness.
  - Annotation: Use annotation tools (e.g., LabelImg) to create bounding box annotations for the tumors in the MRI images. Save annotations in the YOLO format (text files with class and coordinates).
- **Model Selection:** Choose the YOLOv7 architecture, which is optimized for real-time object detection and performs well with fewer computational resources. Download pre-trained weights for YOLOv7 to leverage transfer learning.
- **Training the Model:** Split the dataset into training, validation, and test sets (e.g., 70 percent training, 15 percent validation, 15 percent testing). Configure the YOLOv7 training parameters, including batch size, learning rate, and number of epochs. Train the model using the annotated dataset, monitoring performance metrics like loss and

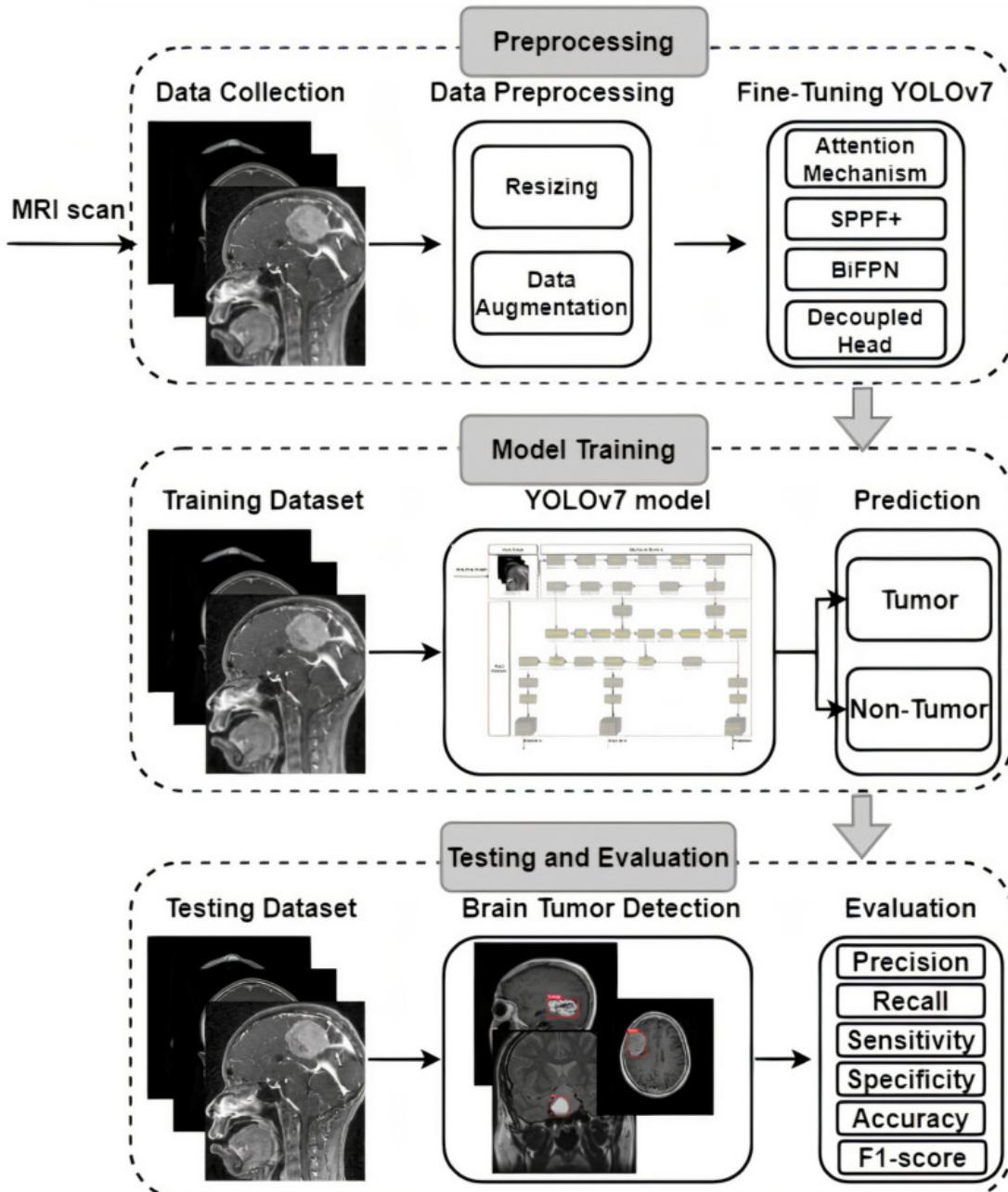


FIGURE 3.3: Overview of the proposed brain tumor detection based on optimized YOLOv7.

mean Average Precision (mAP).

- **Model Evaluation:** Evaluate the model on the test set using metrics such as precision, recall, F1-score, and mAP. Visualize predictions on test images with bounding boxes and class labels to assess performance qualitatively.
- **Post-Processing:** Implement Non-Maximum Suppression (NMS) to filter out duplicate bounding box predictions. Analyze the results to refine the model further or adjust thresholds for classifying tumor presence.
- **Deployment:** Develop a user-friendly application or interface for clinicians to input MRI images and receive real-time tumor detection results. Ensure that the deployment complies with regulatory standards for medical applications.

### 3.4.2 Merits

- **Real-Time Performance:** YOLOv7 is designed for real-time object detection, making it suitable for clinical settings where quick results are essential.
- **High Accuracy:** The architecture achieves high precision and recall rates, particularly effective in detecting small or irregularly shaped tumors.
- **End-to-End Framework:** YOLOv7 provides an end-to-end solution for object detection, reducing the complexity of the pipeline.
- **Scalability:** The model can be scaled to handle large datasets efficiently, suitable for widespread clinical applications.

### 3.4.3 Demerits

- **Data Dependency:** YOLOv7 requires a substantial amount of annotated data for effective training, which can be difficult to obtain in medical imaging.
- **Interpretability Challenges:** Like other deep learning models, YOLOv7 can be seen as a black box, making it hard to interpret the model's decisions.
- **Computational Resources:** While optimized, training the model may still require significant computational resources, especially with larger datasets.
- **Limited Context Understanding:** YOLOv7 focuses on object detection and may not fully capture contextual relationships within the MRI images, which could be important for certain diagnoses.

### 3.5 Enhancing Brain Tumor Classification by a Comprehensive Study on Transfer Learning Techniques and Model Efficiency Using MRI Datasets [5]

Brain tumors, a significant health concern, are a leading cause of mortality globally, with an annual projected increase of 5% by the World Health Organization. This work aims to comprehensively analyze the performance of transfer learning methods in identifying the types of brain tumors, with a particular emphasis on the necessity of prompt identification. The study demonstrates how useful it is to use pre-trained models, including models VGG-16, VGG-19, Inception-v3, ResNet-50, DenseNet, and MobileNet—on MRI datasets and used to obtain a precise classification. Using these methods model accuracy and efficiency have been enhanced.

The research aims to contribute to improved treatment planning and patient outcomes by implementing optimal methodologies for precise and automated brain tumor analysis, evaluation framework encompasses vital metrics such as confusion matrices, ROC curves, and the achieved Area Under the Curve (AUC) for each approach. The comprehensive methodology outlined in this paper serves as a systematic guide for the implementation and evaluation of brain tumor classification models utilizing deep learning techniques. The integration of visual representations, code snippets, and performance metrics significantly enhances the clarity and understanding of the proposed approach. Among our proposed algorithms, VGG-16 attains the highest accuracy at 97 percent and consumes only 22 percent of time as compared to our previous proposed methodology.

This discussion explores pre-trained CNN models' effectiveness in categorizing brain tumor MRI images, employing VGG-16, MobileNet, and ResNet-50. The dataset comprises 3064 brain tumor MRI images from 233 patients, with different image sizes scaled down to  $200 \times 200$  pixels. VGG-16 utilizes  $3 \times 3$  convolution kernels, contributing to 138 million hyperparameters. MobileNet uses modules to reduce convolution layers, while ResNet-50 accommodates numerous layers without increasing training error significantly. The images are preprocessed and assessed using metrics like accuracy and loss.

The analysis uses 2100 scans for training and 900 for validation on a cloud-based GPU virtual machine, displaying predictive graphs based on accuracy and loss over epoch's. Moreover, Recent advancements in medical image processing simplify early disease identification. Medical informatics aids in leveraging extensive medical records. Timely

detection of brain tumors is crucial, in guiding treatment decisions. This study proposes an innovative feature ensemble for accurate MR scan-based tumor classification, outperforming existing methods like CNN-based approaches.

### 3.5.1 Methodology

- **Data Collection:** Gather a dataset of MRI images, including various brain tumor types (e.g., gliomas, meningiomas, pituitary tumors) as well as normal brain images from sources like The Cancer Imaging Archive (TCIA).
- **Data Preprocessing:**
  - Normalization: Scale pixel values to a range of [0, 1] or [-1, 1] to standardize input data for VGG16 or ResNet50.
  - Resizing: Resize images to the required input dimensions (e.g., 224x224 pixels for VGG16 and ResNet50).
  - Data Augmentation: Apply techniques like rotation, horizontal and vertical flipping, and zooming to increase the diversity of the training dataset.
- **Model Selection:** Choose VGG16 or ResNet50: Select one of these pre-trained models based on the specific needs of the task (e.g., complexity, interpretability).
- **Modify the Model:** Replace the final classification layer(s) to match the number of classes in the brain tumor dataset. For example, if there are three classes (normal, glioma, meningioma), adjust the output layer accordingly.
- **Transfer Learning:** Freezing Layers: Decide whether to freeze the initial layers (to retain pre-trained features) or to fine-tune more layers based on the dataset size and complexity.
- **Fine-Tuning:** If fine-tuning, unfreeze the last few layers and train the model on the MRI dataset to adapt it to the specific classification task.
- **Model Training:** Split the dataset into training (70 percent), validation (15 percent), and test (15 percent) sets. Use categorical cross-entropy as the loss function and Adam optimizer for training. Monitor training and validation loss to prevent overfitting, using techniques like early stopping or dropout as needed.
- **Model Evaluation:** Evaluate the model using accuracy, precision, recall, F1-score, and AUC-ROC on the test set. Analyze results with confusion matrices to assess performance across different classes.

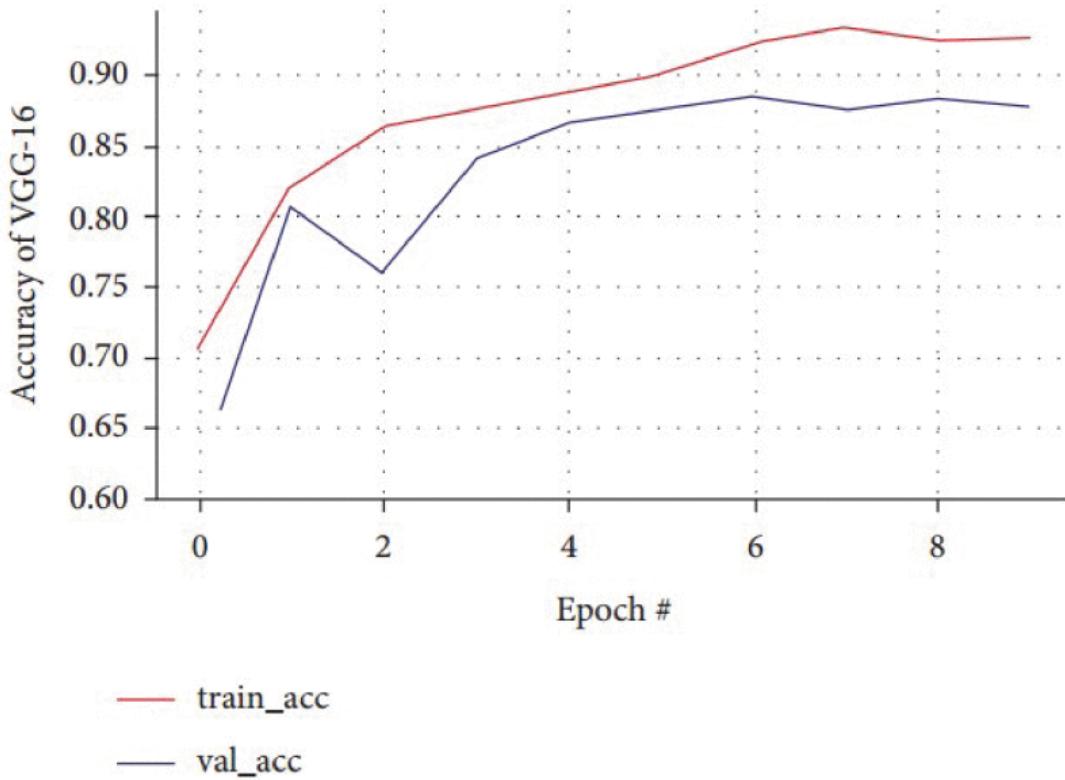


FIGURE 3.4: Training and validation of VGG-16 model.

- **Post-Processing:** Implement techniques for model interpretability, such as Grad-CAM, to visualize the areas of the MRI images that contributed to the predictions. Analyze and refine predictions based on model outputs and visualizations.
- **Deployment:** Develop an application interface for clinicians to input MRI images and receive classification results. Ensure the model complies with medical regulations for clinical deployment.

### 3.5.2 Merits

- **High Accuracy:** Both VGG16 and ResNet50 have demonstrated high accuracy in various image classification tasks, benefiting brain tumor classification significantly.
- **Pre-Trained Features:** Utilizing models pre-trained on large datasets (like ImageNet) allows for better feature extraction and generalization in medical imaging tasks.
- **Transfer Learning Efficiency:** Transfer learning speeds up training and improves model performance, especially useful when working with limited MRI data.
- **Layered Architecture:** ResNet50's residual connections help in training deeper models without vanishing gradients, making it robust for complex image classification tasks.

### 3.5.3 Demerits

- **Data Dependency:** The effectiveness of transfer learning models heavily relies on the quality and representativeness of the dataset; small or biased datasets can lead to overfitting.
- **Interpretability Challenges:** Despite advancements, both models can still be considered black boxes, making it challenging for clinicians to understand model decisions fully.
- **Resource Intensive:** Fine-tuning these models may require significant computational resources, including GPUs, particularly with larger datasets.
- **Limited Context Understanding:** While they perform well on isolated features, these models might struggle with contextual relationships that could impact diagnosis accuracy.

## 3.6 Multiclass Brain Tumor Classification Using Transfer Learning [6]

The human body is made up of trillions of cells. Generally, human cells multiply as the old ones shed off and new ones re-place them. When these cells multiply uncontrollably then it causes cancer. Cancer can be benign and fatal based on its type. There is no restriction for the growth of cancer. It spreads to any part of the body. This spreading to different body parts is called metastasis. These tissues form lumps or tumors that lead to cancer. According to statistics, about 50 percent of deaths are due to late diagnosis and delay in identification. This delay leads to an increase in the mortality rate. In India around 28000 of brain tumor cases are identified annually, out of which 24000 cases are deaths. On calculation around 60 percent of these deaths are caused due to delay in identification.

There are several types of tumors among which pituitary tumor, glioma tumor, meningioma tumor are considered. The former type of tumor develops in the pituitary gland, which is located near the brain, and can affect hormone levels in the body. Pituitary tumors are abnormal growths in the pituitary gland that develop over time. Pituitary tumor can affect the functioning of various hormones as they affect the productivity of that particular hormone. Glioma tumor is also among the regular tumors. This kind of tumor is mostly caused by the glial cells. These cells are non-neural cells but are part of the central nervous system. These cells don't produce any electrical impulses. Glioma tumor effects the functioning of brain such as memory loss, seizures, numbness and many more.

A meningioma is a tumor that develops in the membranes that surround the brain and spinal cord, known as the meninges. Although it is not strictly a brain tumor, it is included in this category since it has the potential to compress or pressure the surrounding brain, nerves, and arteries. This type of tumor occurs. Technology has taken a huge leap where people used to die due to smallpox in ancient times. At present, the medical field has advanced in such a way that cancers are also being treated successfully. Medical devices are implemented to improve the health care in India. These devices play a prominent role in identifying the ailment and treating it with appropriate cure.

Artificial Intelligence has been integrated with the health industries to bring treatment at ease. Communication among patients and doctors residing in different parts of the world has helped lots of people in need of placebo. Deep Learning and Artificial neural networks algorithms have been implemented to classify different types of tumors and their categories. These models have been trained to classify and label the identified illness. These types of models are not only used to classify tumors, but rather in different cases. In this project, the Resnet algorithm has been implemented for image recognition and classification.

Resnet model is built with residual blocks. In these types of blocks, the model is trained up to a few layers and other layers are skipped and then redirected to the output. This type of algorithm reduces the complexity of implementing deep residual neural networks.

### 3.6.1 Methodology

- **Data Collection:** Collect a comprehensive dataset of MRI images, ensuring a variety of brain tumor types (e.g., glioma, meningioma, pituitary tumors) as well as normal images. Use sources like The Cancer Imaging Archive (TCIA) or institutional datasets.

- **Data Preprocessing:**

- Normalization: Scale pixel values to a range of [0, 1] to standardize input for the CNN.
- Resizing: Resize images to a uniform size suitable for the CNN input (e.g., 224x224 pixels).
- Data Augmentation: Implement techniques such as rotation, flipping, zooming, and brightness adjustments to enhance dataset variability and mitigate overfitting.

- **CNN Architecture:** Design a CNN architecture suitable for image classification. A typical architecture may include:

Multiple convolutional layers followed by ReLU activation.

Max pooling layers to reduce spatial dimensions.

Dropout layers to prevent overfitting.

Fully connected layers leading to an output layer with softmax activation for multiclass classification.

- **Model Training:** Split the dataset into training (70%) and testing (30%) sets. Use categorical cross-entropy as the loss function and an optimizer like Adam for training. Monitor training and validation metrics to detect overfitting, adjusting hyperparameters as necessary.

- **Model Evaluation:** Evaluate the model on the test set using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC.

- **Post-Processing:** Implement techniques for model interpretability, such as Grad-CAM, to visualize which parts of the MRI images influenced the model's decisions. Refine predictions and iterate on training based on evaluation insights.

- **Deployment:** Create a user-friendly interface for clinicians to input MRI images and receive classification results.

### 3.6.2 Merits

- **High Accuracy:** CNNs are well-suited for image classification tasks and often achieve high accuracy in distinguishing between different classes of brain tumors.
- **Feature Extraction:** CNNs automatically learn hierarchical features from images, reducing the need for manual feature engineering.
- **Robustness:** With sufficient data augmentation, CNNs can generalize well to variations in MRI image quality and characteristics.
- **Scalability:** The architecture can be adapted and scaled to work with larger datasets and more complex classifications as needed.

### 3.6.3 Demerits

- **Data Dependency:** CNNs require large amounts of labeled training data for effective training; small datasets can lead to overfitting.
- **Computational Resources:** Training CNNs can be resource-intensive, requiring powerful hardware (e.g., GPUs) to achieve reasonable training times.
- **Interpretability Issues:** CNNs are often seen as black boxes, making it challenging for medical professionals to interpret the model's decisions and build trust.
- **Overfitting Risk:** Without careful validation and regularization techniques, models may overfit to the training data, compromising performance on unseen cases.

### 3.7 Optimized Brain Tumor Detection: A Dual-Module Approach for MRI Image Enhancement and Tumor Classification [7]

Neurological and brain-related cancers are one of the main causes of death worldwide. A commonly used tool in diagnosing these conditions is Magnetic Resonance Imaging (MRI), yet the manual evaluation of MRI images by medical experts presents difficulties due to time constraints and variability. This research introduces a novel, two-module computerized method aimed at increasing the speed and accuracy of brain tumor detection. The first module, termed the Image Enhancement Technique, utilizes a trio of machine learning and imaging strategies—adaptive Wiener filtering, neural networks, and independent component analysis—to normalize images and combat issues such as noise and varying low region contrast.

The second module uses Support Vector Machines to validate the output of the first module and perform tumor segmentation and classification. Applied to various types of brain tumors, including meningiomas and pituitary tumors, our method exhibited significant improvements in contrast and classification efficiency. It achieved an average sensitivity and specificity of 0.991, accuracy of 0.989, and a Dice score (DSC) of 0.981. Furthermore, the processing time of our method, averaging at 0.43 seconds, was markedly lower compared to existing methods. These results underscore the superior performance of our approach over current state-of-the-art methods in terms of sensitivity, specificity, precision, and DSC. Future enhancements will seek to increase the robustness of the tumor classification method by employing a standardized approach across a suite of classifiers.

Brain tumors pose significant challenges to healthcare systems worldwide, affecting millions of individuals and contributing to high morbidity and mortality rates. Early and accurate detection of brain tumors is critical for effective treatment and improved patient outcomes. Magnetic Resonance Imaging (MRI) is the gold standard for brain imaging due to its superior contrast resolution and non-invasive nature. However, the quality of MRI images can be adversely affected by noise, artifacts, and variations in acquisition techniques, which can hinder the accurate diagnosis of tumors.

In recent years, advancements in image processing and machine learning have opened new avenues for enhancing the diagnostic capabilities of MRI. Among these advancements, deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as a powerful tool for automating the analysis of medical images. CNNs can

automatically extract complex features from images, enabling precise classification of various brain tumor types.

### 3.7.1 Methodology

- **Data Collection:** Gather a diverse dataset of MRI images featuring various brain tumor types (e.g., glioma, meningioma) and normal brain images from sources like The Cancer Imaging Archive.
- **Image Enhancement Module:**
  - (i) **Adaptive Wiener Filtering:** Apply adaptive Wiener filtering to reduce noise while preserving edges in MRI images. This filtering technique adjusts the filter parameters based on local image characteristics, enhancing the overall image quality.
  - (ii) **Contrast Enhancement:** Use techniques like histogram equalization to improve contrast and make tumors more distinguishable.
  - (iii) **Edge Enhancement:** Apply methods to enhance the visibility of tumor boundaries, which can aid in more accurate feature extraction.
- **Tumor Classification Module:**
  - (i) **Feature Extraction:** Utilize a Convolutional Neural Network (CNN) for automatic feature extraction from the enhanced MRI images. Consider using pre-trained models for transfer learning if applicable.
  - (ii) **Neural Network Training:** Split the dataset into training (70%) and testing (30%) sets. Train the neural network using the enhanced images, employing techniques such as:
    - Categorical cross-entropy as the loss function.
    - Adam or RMSprop as the optimizer.Data augmentation to increase dataset variability and reduce overfitting.
- **Hyperparameter Tuning:** Optimize parameters such as learning rate, batch size, and dropout rates to improve model performance.
- **Model Evaluation:** Evaluate the model using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC. Use confusion matrices to analyze classification performance across different tumor classes.
- **Post-Processing:** Implement visualization techniques like Grad-CAM to show which areas of the MRI images influenced the model's decisions. Analyze and refine model predictions based on evaluation results.
- **Deployment:** Create a user-friendly application for clinicians to upload MRI images and receive enhanced images along with classification results. Ensure compliance with medical regulations for clinical deployment.

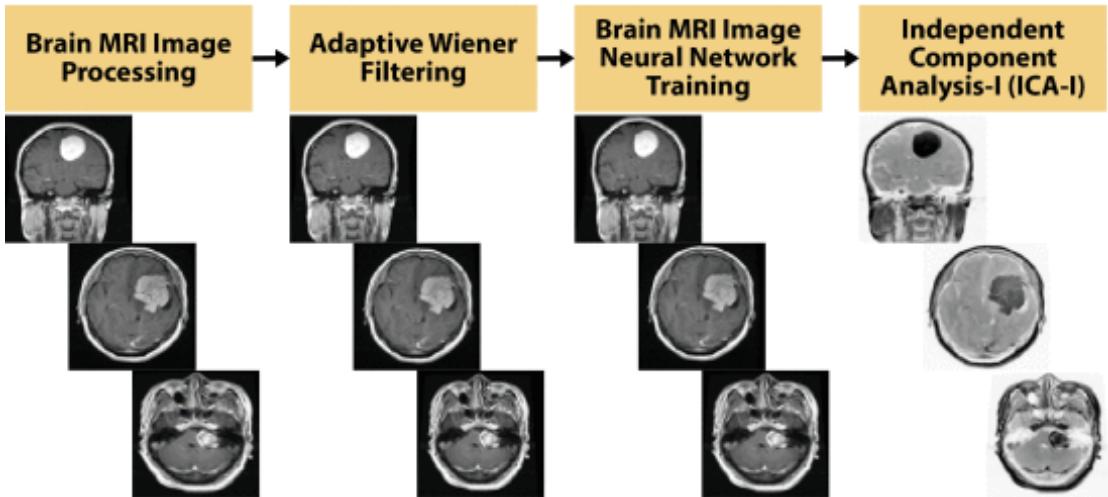


FIGURE 3.5: The proposed model Of Paper 7

### 3.7.2 Merits

- **Enhanced Image Quality:** Adaptive Wiener filtering significantly improves image quality by reducing noise and preserving important features, aiding in better classification.
- **Improved Detection Accuracy:** The combination of image enhancement and CNN-based classification leads to higher accuracy in tumor detection.
- **Robustness:** The approach is robust to variations in MRI image quality, improving generalization across different datasets.
- **Flexibility:** The dual-module approach allows for the integration of advanced image processing techniques with modern deep learning methodologies.

### 3.7.3 Demerits

- **Data Dependency:** The performance of both modules relies heavily on the quality and diversity of the training dataset; small or biased datasets can negatively impact results.
- **Computational Complexity:** Implementing both adaptive filtering and neural network training can be resource-intensive, requiring powerful hardware for efficient processing.
- **Overfitting Risk:** If the model is not properly validated or if the training dataset is small, there is a risk of overfitting, leading to poor performance on unseen images.
- **Interpretability Challenges:** Despite visualization techniques, understanding the underlying decision-making process of deep learning models can remain difficult for clinicians

### 3.8 MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques [8]

Detecting brain tumors in their early stages is crucial. Brain tumors are classified by biopsy, which can only be performed through definitive brain surgery. Computational intelligence-oriented techniques can help physicians identify and classify brain tumors. Herein, we proposed two deep learning methods and several machine learning approaches for diagnosing three types of tumor, i.e., glioma, meningioma, and pituitary gland tumors, as well as healthy brains without tumors, using magnetic resonance brain images to enable physicians to detect with high accuracy tumors in early stages.

In medical terms, tumors are known as malignant or benign neoplasms, of which there are more than 200 diverse varieties that may affect humans [1]. According to the American Cancer Society, a brain tumor is a severe disease in which irregular brain tissue growth impairs brain function. The National Brain Tumor Foundation (NBTF) reported that the number of people who have lost their lives due to brain tumors has increased by 300% in the last three decades

A dataset containing 3264 Magnetic Resonance Imaging (MRI) brain images comprising images of glioma, meningioma, pituitary gland tumors, and healthy brains were used in this study. First, preprocessing and augmentation algorithms were applied to MRI brain images. Next, we developed a new 2D Convolutional Neural Network (CNN) and a convolutional auto-encoder network, both of which were already trained by our assigned hyperparameters.

Then 2D CNN includes several convolution layers; all layers in this hierarchical network have a  $2 \times 2$  kernel function. This network consists of eight convolutional and four pooling layers, and after all convolution layers, batch-normalization layers were applied. The modified auto-encoder network includes a convolutional auto-encoder network and a convolutional network for classification that uses the last output encoder layer of the first part.

In medical terms, tumors are known as malignant or benign neoplasms, of which there are more than 200 diverse varieties that may affect humans. According to the American Cancer Society, a brain tumor is a severe disease in which irregular brain tissue growth impairs brain function. The National Brain Tumor Foundation (NBTF) reported that the number of people who have lost their lives due to brain tumors has increased by 300% in the last three decades . Brain tumors can lead to death if left untreated.

The complexity of brain tumors poses challenges for healthcare providers in diagnosing and caring for affected patients. Early detection of brain tumors and initiation of treatment play vital roles in the survival rate of these patients. Brain tumor biopsy is not as easy as biopsy of other parts of the body, as it must be performed with surgery. Therefore, the need for another method for accurate diagnosis without surgery is crucial. Magnetic Resonance Imaging (MRI) is the best and most commonly used option for diagnosing brain tumors .

The present study shows that the proposed 2D CNN has optimal accuracy in classifying brain tumors. Comparing the performance of various CNNs and machine learning methods in diagnosing three types of brain tumors revealed that the 2D CNN achieved exemplary performance and optimal execution time without latency. This proposed network is less complex than the auto-encoder network and can be employed by radiologists and physicians in clinical systems for brain tumor detection.

### 3.8.1 Methodology

- **Data Collection:** Utilize a diverse dataset of MRI images featuring various brain tumors (e.g., glioma, meningioma, pituitary tumors) and normal brain scans. Source images from publicly available datasets or medical institutions.
- **Data Preprocessing:**
  - Normalization: Normalize pixel values to a consistent range (e.g., [0, 1]) to prepare the data for the neural network.
  - Resizing: Resize images to a fixed size (e.g., 224x224 pixels) to match the input requirements of the 2D CNN architecture.
  - Data Augmentation: Apply techniques such as rotation, flipping, zooming, and brightness adjustments to increase the variability of the training dataset and reduce overfitting.
- **2D CNN Architecture:** Design a CNN model comprising several convolutional layers followed by activation functions (typically ReLU). Implement pooling layers (e.g., Max Pooling) after convolutional layers to downsample feature maps, reducing dimensionality while retaining important features. Add one or more fully connected layers at the end to combine the features learned by the CNN and produce output probabilities for each tumor class.
- **Training Process:** Split the dataset into training (70Train the 2D CNN using a suitable loss function (e.g., categorical cross-entropy) and an optimizer (e.g., Adam). Monitor performance on the validation set to avoid overfitting, adjusting hyperparameters as necessary.
- **Model Evaluation:** Evaluate the model's performance on the test set using metrics

such as accuracy, precision, recall, F1-score, and AUC-ROC. Use confusion matrices to analyze misclassifications across different tumor classes.

- **Post-Processing:** Utilize visualization techniques (e.g., Grad-CAM) to interpret model predictions, highlighting regions of the MRI images that influenced the classification decisions.
- **Deployment:** Create a user-friendly interface for clinicians to upload MRI images and receive classification results, ensuring compliance with regulatory standards for clinical use.

### 3.8.2 Merits

- **High Accuracy:** 2D CNNs are capable of achieving high accuracy in image classification tasks, which is crucial for reliable brain tumor detection.
- **Automatic Feature Extraction:** CNNs automatically learn relevant features from MRI images, reducing the need for manual feature engineering and allowing the model to adapt to varying data characteristics.
- **Robust Performance:** The architecture is robust to variations in MRI image quality and can handle noise effectively due to the hierarchical feature extraction process.
- **Scalability:** The model can be scaled and fine-tuned for different types of tumors and datasets, making it versatile for various clinical applications.

### 3.8.3 Demerits

- **Data Dependency:** The effectiveness of 2D CNNs is heavily dependent on the size and diversity of the training dataset. Limited datasets can lead to overfitting and reduced generalization to unseen data.
- **Computational Resources:** Training deep learning models, particularly CNNs, requires significant computational power, often necessitating access to GPUs for efficient processing.
- **Interpretability Challenges:** Despite advancements in visualization techniques, CNNs are often seen as black boxes, making it difficult for clinicians to understand the reasoning behind specific predictions.
- **Hyperparameter Sensitivity:** The performance of CNNs can be sensitive to hyperparameter choices (e.g., learning rate, batch size), which requires careful tuning and validation.

### 3.9 Brain tumor detection from images and comparison with transfer learning methods and 3-layer CNN [9]

The healthcare industry has been rapidly transformed by technological advances in recent years, and an important component of this transformation is artificial intelligence (AI) technology. AI is a computer system that simulates human-like intelligence and has many applications in medicine. One such area is the fight against brain tumors. Brain tumors are a major public health problem in the healthcare sector, and accurate diagnosis, treatment, and follow-up processes are critical.

AI has become an important tool for improving these processes and has great potential for early diagnosis and treatment of brain tumors. Brain tumors affect human health due to their location. . AI is designed to help diagnose and treat complex diseases such as brain tumors by combining technologies such as big data analytics, machine learning, and deep learning.

AI has the ability to detect and classify tumors by analyzing brain imaging techniques, such as Magnetic Resonance Imaging (MRI). AI algorithms can help determine the size, location, class, and aggressiveness of tumors. This helps physicians make a more accurate diagnosis and treatment plan, and helps patients better understand their health. AI can also be used to track a patient's progress through treatment.

AI-based analytics can be used to assess treatment response and predict potential tumor recurrence. In this way, patients' treatment plans can be more effectively organized and individualized treatment approaches can be developed. In this study, difference detection was performed on brain images. Classification was performed with multilayer CNN and CNN-based transfer learning methods on 4 classes labeled by physicians.

Diagnosis for human health is provided by magnetic resonance imaging (MRI) devices, which help health decision makers in critical organs such as brain health. Images from these devices are a source of big data for artificial intelligence. This big data enables high performance in image processing classification problems, which is a subfield of artificial intelligence. In this study, we aim to classify brain tumors such as glioma, meningioma, and pituitary tumor from brain MR images.

Convolutional Neural Network (CNN) and CNN-based inception-V3, EfficientNetB4, VGG19, transfer learning methods were used for classification. F-score, recall, imprinting and accuracy were used to evaluate these models. The best accuracy result was obtained with VGG16 with 98% while the F-score value of the same transfer learning model was 97%, the Area Under the Curve (AUC) value was 99%, the recall value was

98%, and the precision value was 98%. CNN architecture and CNN-based transfer learning models are very important for human health in early diagnosis and rapid treatment of such diseases.

### 3.9.1 Methodology

- **Data Collection:** Obtain a dataset of brain MRI images containing various tumor types (e.g., glioma, meningioma, and normal brain images) from public medical databases or clinical sources.
- **Data Preprocessing:**
  - Normalization: Normalize pixel values to a standard range (e.g., [0, 1]) to prepare for neural network input.
  - Resizing: Resize images to a consistent dimension (e.g., 224x224 pixels) to ensure uniformity across the dataset.
  - Augmentation: Implement techniques such as rotation, flipping, scaling, and contrast adjustments to enhance dataset variability and mitigate overfitting.
- **Model Development:**
  - **3-Layer CNN Architecture:**
    - Input Layer: Accepts the preprocessed images.
    - Convolutional Layers: Use three convolutional layers to extract features from the images, applying ReLU activation functions after each convolution.
    - Pooling Layers: Insert pooling layers (e.g., Max Pooling) after each convolution to reduce dimensionality and retain important features.
    - Fully Connected Layer: Conclude with a fully connected layer that outputs the probability distribution across the tumor classes (normal vs. tumor types).
  - **Transfer Learning Methods:** Select a pre-trained model (e.g., VGG16, ResNet50) as a starting point for comparison. Fine-tune the pre-trained model on the same dataset, allowing the network to adapt to the specific features of the MRI images. Freeze the initial layers of the pre-trained model and retrain only the final layers to optimize for the brain tumor classification task.
  - **Training Process:** Split the dataset into training (typically 70%), validation (15%), and testing (15%) sets. Train both the 3-layer CNN and the transfer learning model using appropriate loss functions (e.g., categorical cross-entropy) and optimizers (e.g., Adam). Monitor performance during training to prevent overfitting.
  - **Model Evaluation:** Evaluate the performance of both models using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC. Use confusion matrices to assess the models' classification performance across different tumor types.
  - **Comparison and Analysis:** Compare the results from the 3-layer CNN and the

transfer learning models to determine which approach yields better performance. Analyze the strengths and weaknesses of each method based on the evaluation metrics.

### 3.9.2 Merits

- **Performance Comparison:** This methodology allows for a direct comparison between a custom-built CNN and established transfer learning techniques, providing insights into their relative strengths.
- **High Accuracy:** Transfer learning often leads to higher accuracy due to the utilization of pre-trained features from larger datasets, enhancing performance on smaller datasets.
- **Resource Efficiency:** Using a 3-layer CNN requires less computational power compared to deeper architectures, making it accessible for environments with limited resources.
- **Flexibility:** The architecture can be easily modified to include additional layers or different types of architectures based on performance outcomes.

### 3.9.3 Demerits

- **Data Requirement:** The performance of both the 3-layer CNN and transfer learning approaches is heavily dependent on the quantity and quality of the training data; small datasets can lead to overfitting.
- **Training Time:** While transfer learning can save time due to pre-trained weights, fine-tuning still requires significant computational resources and training time, especially with larger models.
- **Interpretability Challenges:** Both models, particularly the transfer learning models, can be difficult to interpret, making it challenging for clinicians to understand the decision-making process.
- **Limited Complexity in 3-Layer CNN:** A 3-layer CNN may lack the capacity to learn complex features compared to deeper networks, potentially limiting its performance on challenging classification tasks.

### 3.10 Employing deep learning and transfer learning for accurate brain tumor detection [10]

Artificial intelligence-powered deep learning methods are being used to diagnose brain tumors with high accuracy, owing to their ability to process large amounts of data. Magnetic resonance imaging stands as the gold standard for brain tumor diagnosis using machine vision, surpassing computed tomography, ultrasound, and X-ray imaging in its effectiveness. Despite this, brain tumor diagnosis remains a challenging endeavour due to the intricate structure of the brain. This study delves into the potential of deep transfer learning architectures to elevate the accuracy of brain tumor diagnosis. Transfer learning is a machine learning technique that allows us to repurpose pre-trained models on new tasks. This can be particularly useful for medical imaging tasks, where labelled data is often scarce. Four distinct transfer learning architectures were assessed in this study: ResNet152, VGG19, DenseNet169, and MobileNetv3. The models were trained and validated on a dataset from benchmark database: Kaggle. Five-fold cross validation was adopted for training and testing. To enhance the balance of the dataset and improve the performance of the models, image enhancement techniques were applied to the data for the four categories: pituitary, normal, meningioma, and glioma. MobileNetv3 achieved the highest accuracy of 99.75%. This demonstrates the potential of deep transfer learning architectures to revolutionize the field of brain tumor diagnosis.

The early and accurate detection of brain tumors is crucial for effective treatment and improved patient outcomes, with Magnetic Resonance Imaging (MRI) serving as the primary imaging modality in clinical practice. Recent advancements in deep learning, particularly convolutional neural networks (CNNs) and transfer learning techniques, have revolutionized medical image analysis, enabling automated and highly accurate tumor classification from MRI scans. By leveraging pre-trained models that capture complex features from vast datasets, these methods can significantly enhance the performance of tumor detection systems, reducing the dependency on large labeled datasets while maintaining high accuracy. This paper explores the application of deep learning and transfer learning in brain tumor detection, highlighting the effectiveness of these techniques in improving diagnostic capabilities and offering insights into their implementation challenges and clinical relevance.

#### 3.10.1 Methodology

- **Data Collection:** Gather a comprehensive dataset of MRI images containing various types of brain tumors (e.g., glioma, meningioma, metastatic tumors) along with

normal brain scans. Utilize publicly available datasets such as The Cancer Imaging Archive (TCIA) or collaborate with medical institutions for clinically obtained images.

- **Data Preprocessing:**

- Normalization: Normalize the pixel values of the MRI images to a standard range (e.g., [0, 1]) to enhance model training.
- Resizing: Resize all images to a consistent dimension (e.g., 224x224 pixels) to meet the input requirements of the chosen deep learning models.
- Data Augmentation: Apply techniques like rotation, flipping, zooming, and brightness adjustments to increase dataset variability and reduce the risk of overfitting.

- **Deep Learning Model Development:** Architecture Selection: Choose suitable deep learning architectures such as Convolutional Neural Networks (CNNs) or more complex models like ResNet, VGG16, or Inception. Model Configuration: Configure the chosen architecture with multiple convolutional layers, pooling layers, and fully connected layers, culminating in a softmax output layer for classification.

- **Transfer Learning:** Select a pre-trained model that has been trained on a large dataset (e.g., ImageNet).

Fine-tune the model on the brain MRI dataset by: Replacing the output layer to match the number of classes (tumor types and normal). Freezing the initial layers to retain learned features and retraining the final layers to adapt to the specific features of the brain MRI images.

- **Training Process:** Split the dataset into training (typically 70%), validation (15%), and testing (15%) sets. Train the model using appropriate loss functions (e.g., categorical cross-entropy) and optimizers (e.g., Adam). Monitor performance on the validation set to prevent overfitting, using techniques such as early stopping or dropout regularization.

- **Model Evaluation:** Evaluate the trained model on the test set using metrics like accuracy, precision, recall, F1-score, and AUC-ROC. Analyze classification results through confusion matrices to identify misclassifications among different tumor types.

- **Post-Processing and Visualization:** Use techniques like Grad-CAM to visualize which areas of the MRI images the model focused on when making predictions. Provide insights into the interpretability of the model's decisions to assist clinicians.

### 3.10.2 Merits

- **High Accuracy:** Deep learning, particularly when combined with transfer learning, often leads to superior accuracy in brain tumor detection due to the ability to leverage learned features from large datasets.

- **Reduced Training Time:** Transfer learning significantly reduces training time as

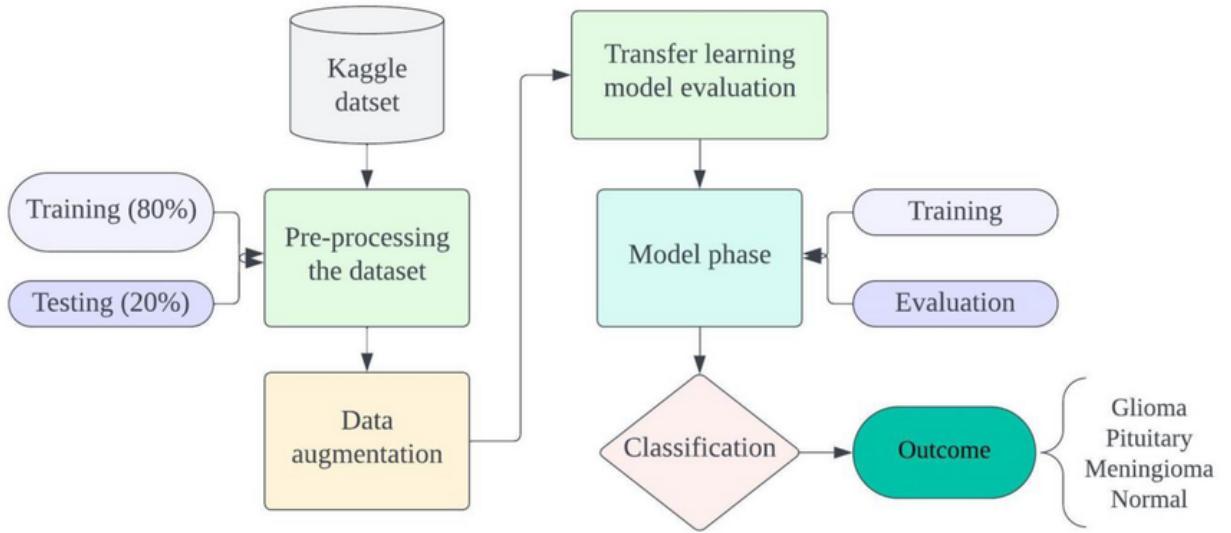


FIGURE 3.6: Proposed model architecture.

it allows the model to start with pre-trained weights, requiring less data for effective learning.

- **Effective Feature Extraction:** Deep learning models automatically extract complex features from images, reducing the need for manual feature engineering and enabling adaptation to diverse datasets.
- **Scalability:** The approach can be scaled to accommodate additional tumor types or image modalities, enhancing its applicability in clinical settings.

### 3.10.3 Demerits

- **Data Dependency:** While transfer learning mitigates the need for large datasets, the performance still heavily relies on the quality and diversity of the training data; small or biased datasets can lead to overfitting.
- **Computational Resources:** Training deep learning models requires significant computational power, often necessitating access to GPUs or specialized hardware.
- **Interpretability Challenges:** Despite advancements in visualization techniques, deep learning models can still act as black boxes, making it difficult for clinicians to fully understand the basis of their predictions.
- **Hyperparameter Sensitivity:** The effectiveness of the model can be sensitive to the choice of hyperparameters (e.g., learning rate, batch size), necessitating careful tuning and validation.

### 3.11 Brain Tumor Classification Using Deep Learning Algorithms [11]

A brain tumor, known as an intracranial tumor, is a surplus growth of brain tissue in which cells grow and multiply uncontrollably, seemingly unchecked by the immune system. The foremost reason the human body is unable to recognize and fight these cells is that it cannot identify them as foreign objects. This is because these types of cells encompass the patient's DNA, which the body's immune system recognizes as natural.

The World Health Organization (WHO) classifies brain tumors as grade I-IV. Where benign tumors are Grade I which are slow-growing, least harmful, and easily curable. Malignant Tumor is Grade III. These types of tumors tend to be a bit infiltrative and have chances of recurrence at a higher grade too. A pituitary tumor is a growth of abnormal cells in the tissues of the pituitary gland. While almost all Pituitary Tumors are benign because they don't spread to other parts of the body, as cancers can, they are close to the brain and may invade the central nervous system (CNS) or to other parts of the body. There is no standard grading system for pituitary tumors unlike the other above-mentioned.

As explained above, early detection of these brain tumors is extremely important as these tumors tend to metastasize and grow rapidly. Furthermore, after identification, the classification stage may be a convoluted and tedious task for physicians or radiologists in some complicated cases and completely depends on the availability of expert physicians and radiologists, which is difficult to fulfill in underdeveloped and few developing regions around the globe.

These cases need experts to work on, localize the tumor, compare tumor tissues with adjacent regions, apply various filters on the image if necessary; make it more clear for human vision, and finally conclude; whether it is a tumor besides its type and grade if available. This quick and accurate detection can be achieved through groundbreaking technological advancement in the field of Artificial Intelligence, which has shown promises of higher accuracies in the field of computer vision, image classification, and image segmentation.

Deep learning is a subdivision of Machine Learning where a system of neural networks which mimic the human brain structure are trained with huge amounts of data. These types of supervised, semi-supervised, or unsupervised networks have shown tremendous potential in the fields of medical image analysis. These networks are divided into several layers, where the first layer is known as the input layer, the internal layers are known as the hidden layers and the final layer is known as the output layer. Deep learning

algorithms utilize these arrangements of numerous layers of the network for feature extraction and encoding.

The output of each sequential layer is the input of the succeeding one, and that helps in data abstraction as we go deep within the network. Artificial Neural Networks, Convolution Neural Networks are two popular types of neural nets that are widely used in the industry today. Generally, CNN's are preferred for image classification tasks as they implement feature selection that happens through convolving filters and pooling with the input patterns followed by a selection of the most distinguishing features and then start to train the layers of the classification network.

Convolution Neural Networks outperform simple Artificial Neural Networks for medical image classification of Brain Tumors into given four classes of: No Tumor, Benign Tumor, Malignant Tumor or Pituitary Tumor. Our dataset consisted of 3190 two-dimensional T1-weighted contrastenhanced images which were then pre-processed, cropped and augmented. The dataset included three different views of MRI: axial, coronal and sagittal views.

After training multiple models on this cleaned augmented data, the best ANN model had an accuracy of 78%, loss of 181.14 and a F1 Score of 78. While out of the total 27 CNN models that we trained, the best CNN model with 3 convolution layers had an accuracy of 90%, loss of 0.43 and F1 Score of 91. This also re-trained some pre-existing models from Keras library. Out of which the best TL model was - VGG16 which was re-trained on our augmented dataset had the highest accuracy among all models. On test data, VGG16 had the accuracy of 94%, a loss value of 0.81 and F1 Score of 94. Thus from the above results, we can conclude that models with convolution layers(CNN, TL) are better than models without convolution layers(ANN) for medical image classification of brain tumors using MRI images.

### 3.11.1 Methodology

- **Dataset Selection:** The study utilizes publicly available MRI datasets, consisting of labeled images for different types of brain tumors.
- **Preprocessing:** Image resizing and normalization to ensure uniform input dimensions. Data augmentation techniques to enhance model generalization.
- **Deep Learning Model (CNN-based approach):** A Convolutional Neural Network (CNN) is implemented to extract spatial and textural features from MRI scans. The architecture includes convolutional layers, pooling layers, and fully connected layers for feature extraction and classification. Softmax activation is used for final classification.

- **Training and Evaluation:** The model is trained using supervised learning, with cross-entropy loss and an Adam optimizer. Performance is evaluated using accuracy, precision, recall, and F1-score.

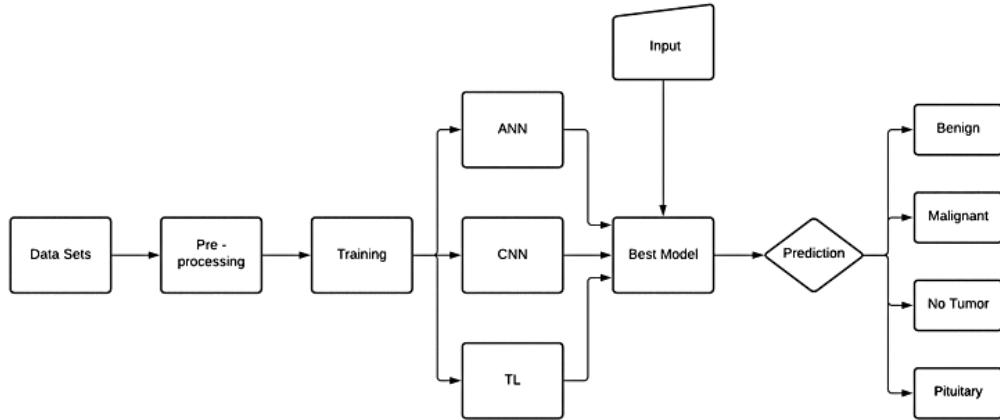


FIGURE 3.7: System Architecture Of Paper 11

### 3.11.2 Merits

- **High Accuracy:** CNN-based classification significantly improves accuracy over traditional manual methods. Automation: Reduces the dependency on radiologists and speeds up the diagnosis process.
- **Feature Extraction:** Deep learning eliminates the need for manual feature extraction, making it more efficient.
- **Generalization:** Data augmentation techniques improve the model's ability to classify unseen images.

### 3.11.3 Demerits

- **Computational Complexity:** CNNs require high computational power, making them expensive to deploy in real-time hospital settings.
- **Limited Dataset:** The model's performance heavily depends on the quality and diversity of the training dataset.
- **Lack of Explainability:** Deep learning models function as black boxes, making it difficult for medical professionals to interpret the decision-making process.
- **Overfitting Risk:** Without proper regularization techniques, the model may perform well on training data but struggle with real-world cases.

### 3.12 You Only Look Once: Unified, Real-Time Object Detection [12]

Humans glance at an image and instantly know what objects are in the image, where they are, and how they interact. The human visual system is fast and accurate, allowing us to perform complex tasks like driving with little conscious thought. Fast, accurate algorithms for object detection would allow computers to drive cars without specialized sensors, enable assistive devices to convey real-time scene information to human users, and unlock the potential for general purpose, responsive robotic systems. Current detection systems repurpose classifiers to perform detection. To detect an object, these systems take a classifier for that object and evaluate it at various locations and scales in a test image. Systems like deformable parts models (DPM) use a sliding window approach where the classifier is run at evenly spaced locations over the entire image.

More recent approaches like R-CNN use region proposal methods to first generate potential bounding boxes in an image and then run a classifier on these proposed boxes. After classification, post-processing is used to refine the bounding boxes, eliminate duplicate detections, and rescore the boxes based on other objects in the scene . These complex pipelines are slow and hard to optimize because each individual component must be trained separately. We reframe object detection as a single regression problem, straight from image pixels to bounding box coordinates and class probabilities. Using our system, you only look once (YOLO) at an image to predict what objects are present and where they are.

YOLO is refreshingly simple. A single convolutional network simultaneously predicts multiple bounding boxes and class probabilities for those boxes. YOLO trains on full images and directly optimizes detection performance. This unified model has several benefits over traditional methods of object detection. First, YOLO is extremely fast. Since we frame detection as a regression problem we don't need a complex pipeline. We simply run our neural network on a new image at test time to predict detections. Our base network runs at 45 frames per second with no batch processing on a Titan X GPU and a fast version runs at more than 150 fps. This means we can process streaming video in real-time with less than 25 milliseconds of latency. Furthermore, YOLO achieves more than twice the mean average precision of other real-time systems.

### 3.12.1 Methodology

- **Single Neural Network Architecture :** YOLO processes the entire image in a single pass using a fully convolutional network (FCN). The image is divided into an  $S \times S$  grid, where each grid predicts bounding boxes and class probabilities. This differs from traditional object detection, where region proposals and classification are separate steps.
- **Bounding Box Prediction :** Instead of generating thousands of region proposals like R-CNN, YOLO predicts a fixed number of bounding boxes with confidence scores. This is done in parallel, significantly reducing inference time.
- **Loss Function :** Uses a custom multi-part loss function combining classification loss, localization loss, and confidence loss. Encourages better bounding box predictions and suppresses false positives.
- **Trade-off Between Speed and Accuracy :** YOLO outperforms traditional methods in terms of speed (real-time detection at 45 FPS) but has a trade-off in accuracy compared to R-CNN variants.

### 3.12.2 Merits

- **Real-time Object Detection:** Can detect objects at high FPS ( 45 FPS on GPU), making it suitable for real-world applications.
- **End-to-End Training:** Unlike R-CNN, which requires multiple models (region proposal + classification), YOLO is fully trainable in a single neural network.
- **Global Context Awareness:** YOLO sees the entire image, making it less prone to background false positives.
- **Efficient:** YOLO processes images significantly faster than region-based methods like Faster R-CNN.

### 3.12.3 Demerits

- **Lower Accuracy in Small Objects:** Struggles with detecting small and overlapping objects due to its fixed grid-based predictions.
- **Less Precise Localization:** Bounding box predictions are coarser than anchor-based methods like Faster R-CNN.
- **Sensitivity to Aspect Ratios:** YOLO has difficulty with objects of varying sizes due to its fixed grid system.

### 3.13 Multi-Classification of Brain Tumor Images Using Deep Neural Network [13]

Brain tumor classification is a crucial task to evaluate the tumors and make a treatment decision according to their classes. There are many imaging techniques used to detect brain tumors. However, MRI is commonly used due to its superior image quality and the fact of relying on no ionizing radiation. Deep learning (DL) is a subfield of machine learning and recently showed a remarkable performance, especially in classification and segmentation problems.

In this paper, a DL model based on a convolutional neural network is proposed to classify different brain tumor types using two publicly available datasets. The former one classifies tumors into (meningioma, glioma, and pituitary tumor). The other one differentiates between the three glioma grades (Grade II, Grade III, and Grade IV). The datasets include 233 and 73 patients with a total of 3064 and 516 images on T1-weighted contrast-enhanced images for the first and second datasets, respectively. The proposed network structure achieves a significant performance with the best overall accuracy of 96.13% and 98.7%, respectively, for the two studies. The results indicate the ability of the model for brain tumor multi-classification purposes.

Brain tumors are one of the most life-threatening conditions, requiring precise classification for accurate diagnosis and effective treatment planning. Early detection and classification play a crucial role in improving patient outcomes by enabling timely interventions. Magnetic Resonance Imaging (MRI) is widely used in medical imaging for brain tumor diagnosis due to its superior image quality and non-invasive nature, avoiding the risks associated with ionizing radiation.

In recent years, deep learning (DL), a subfield of machine learning, has demonstrated exceptional performance in various medical imaging tasks, particularly in classification and segmentation problems. Convolutional Neural Networks (CNNs) have emerged as a powerful tool for automating the process of tumor detection and classification, reducing human intervention while enhancing accuracy and efficiency.

This study presents a DL-based CNN model for brain tumor classification, utilizing two publicly available datasets. The first dataset classifies brain tumors into three types: meningioma, glioma, and pituitary tumor, while the second dataset focuses on differentiating between three glioma grades (Grade II, Grade III, and Grade IV). The datasets contain MRI images obtained using T1-weighted contrast-enhanced imaging, which provides detailed visualization of tumor structures.

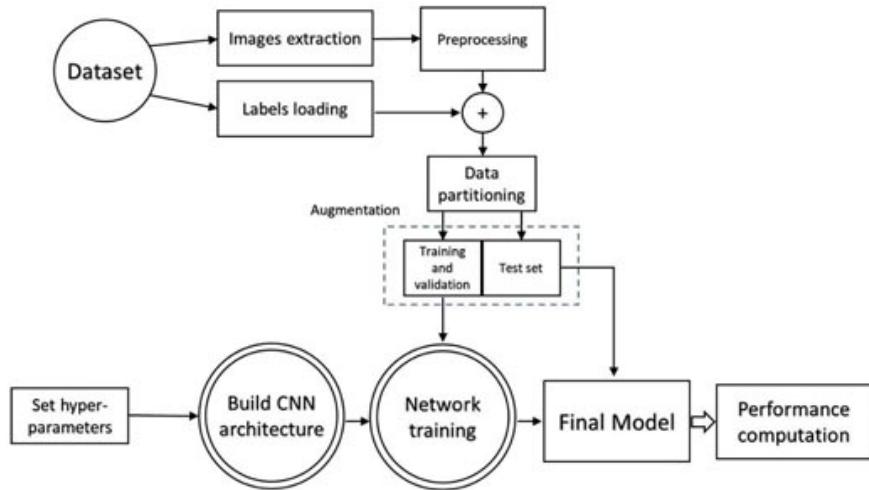


FIGURE 3.8: Block diagram of the proposed method

The proposed CNN model achieves high classification accuracy of 96.13% and 98.7% for the two datasets, respectively, demonstrating its potential for multi-class brain tumor classification. These results indicate that deep learning-based automated systems can significantly enhance the accuracy and efficiency of brain tumor diagnosis, assisting medical professionals in making informed treatment decisions.

### 3.13.1 Methodology

- **Dataset Preparation and Augmentation :** The dataset includes T1-weighted contrast-enhanced MRI images. Data augmentation techniques such as rotation, flipping, and contrast enhancement are applied to improve the model's generalization.
- **Deep Learning Model :** A custom CNN architecture is used to classify brain tumors into three categories. The model consists of multiple convolutional layers, pooling layers, and fully connected layers to extract tumor features.
- **Training and Optimization :** The model is trained using Adam optimizer with categorical cross-entropy loss. The dataset is split into training (80%) and testing (20%) to evaluate performance.
- **Evaluation Metrics :** Performance is measured using accuracy, precision, recall, F1-score, and confusion matrix. The model achieves high accuracy compared to traditional machine learning techniques.

### 3.13.2 Merits

- **High Accuracy:** The deep CNN model outperforms traditional machine learning models.

- **Automated Tumor Classification:** Reduces reliance on manual diagnosis, which is prone to errors.
- **Efficient MRI Image Preprocessing:** Preprocessing steps enhance image quality, improving classification accuracy.
- **Robust Model Performance:** Shows strong generalization with high accuracy and F1-score.

### 3.13.3 Demerits

- **Computationally Expensive:** Deep CNNs require high processing power and GPU acceleration.
- **Limited Dataset:** The study focuses on a single dataset, which may not generalize well to different MRI scans.
- **No Real-time Implementation:** The approach lacks real-time segmentation capabilities (e.g., using YOLOv8).

# CHAPTER 4

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## System Design And Implementation

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Brain tumor detection is a critical task in medical imaging, requiring accurate identification and classification of tumor types. This system leverages deep learning models to automate tumor segmentation and classification using MRI scans. By integrating YOLO for tumor detection and EfficientNet B0 for classification, the approach enhances diagnostic accuracy and efficiency in medical applications.

### 4.1 System Architecture

#### 4.1.1 Dataset Collection

Obtain a labeled dataset containing MRI brain scan images with tumor categories (Glioma, Meningioma, Pituitary Tumor, and No Tumor). Common sources include publicly available datasets like BraTS (Brain Tumor Segmentation Challenge) or Kaggle datasets. Ensure the dataset includes images in DICOM, PNG, or JPG format with corresponding labels.

#### 4.1.2 Image Preprocessing

Convert all images into a standard format (e.g., 224x224 pixels) for uniform processing. Grayscale conversion is applied to remove color variations and retain only structural details. Perform intensity normalization to adjust pixel values, ensuring uniform brightness and contrast across all images.

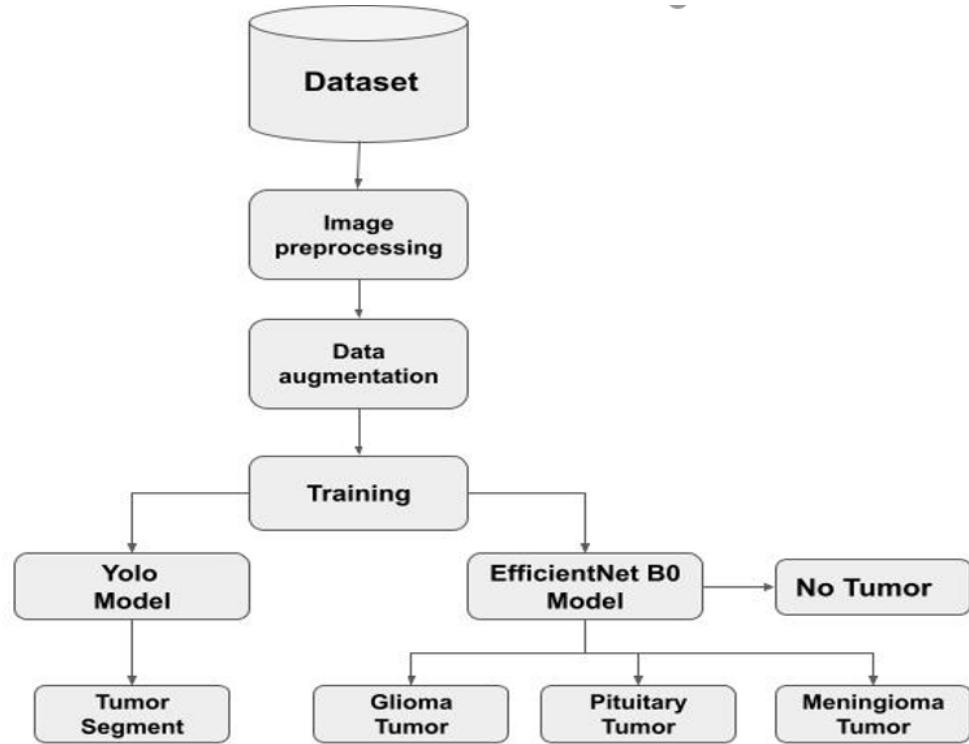


FIGURE 4.1: System Architecture

#### 4.1.3 Data Augmentation

Apply transformations such as rotation ( $\pm 20^\circ$ ), flipping (horizontal/vertical), and zooming (10-20 percentage) to increase dataset diversity. Adjust image contrast and brightness to simulate real-world variations in MRI scans. Augmented images are stored in a new dataset, ensuring a balanced number of samples for each tumor type.

#### 4.1.4 Training Phase

The system trains two deep learning models: YOLO for segmentation and EfficientNet B0 for classification. The dataset is split into 80 percent training, 10 percent validation, and 10 percent testing. Training is performed on a GPU-enabled system for faster computations.

#### 4.1.5 Tumor Segmentation using YOLO Model

Input: MRI images after preprocessing and augmentation. YOLO (You Only Look Once) detects tumor regions and places bounding boxes around them. The model is

trained using a combination of Binary Cross-Entropy and IoU loss functions for accurate segmentation.

#### 4.1.6 Tumor Classification using EfficientNet B0

Input: Tumor-segmented images obtained from YOLO. EfficientNet B0 classifies images into four categories: Glioma, Meningioma, Pituitary Tumor, or No Tumor. The model is trained using Categorical Cross-Entropy loss function and the Adam optimizer.

#### 4.1.7 Model Evaluation and Testing

The trained models are tested using the remaining 10 percent test data to assess performance. Evaluation metrics such as accuracy, precision, recall, and F1-score are computed. If performance is suboptimal, hyperparameters are fine-tuned, and models are retrained with adjusted settings.

#### 4.1.8 Final Prediction and Diagnosis

Given a new MRI image, the YOLO model first segments the tumor (if present). If a tumor is detected, EfficientNet B0 classifies it as Glioma, Meningioma, or Pituitary Tumor. If no tumor is detected, the image is classified as "No Tumor", and the process ends.

#### 4.1.9 Deployment and Integration

The trained model is deployed using a web-based or desktop application for real-time MRI analysis. The system can be integrated into hospitals or diagnostic centers for automated brain tumor detection. Further improvements can include real-time processing with cloud integration for scalability.

## 4.2 CNN Architecture

This is a Convolutional Neural Network (CNN) architecture for brain tumor classification from MRI images.

### 1. Input Layer:

The model receives a brain MRI scan as input, resized to  $32 \times 32$  pixels for

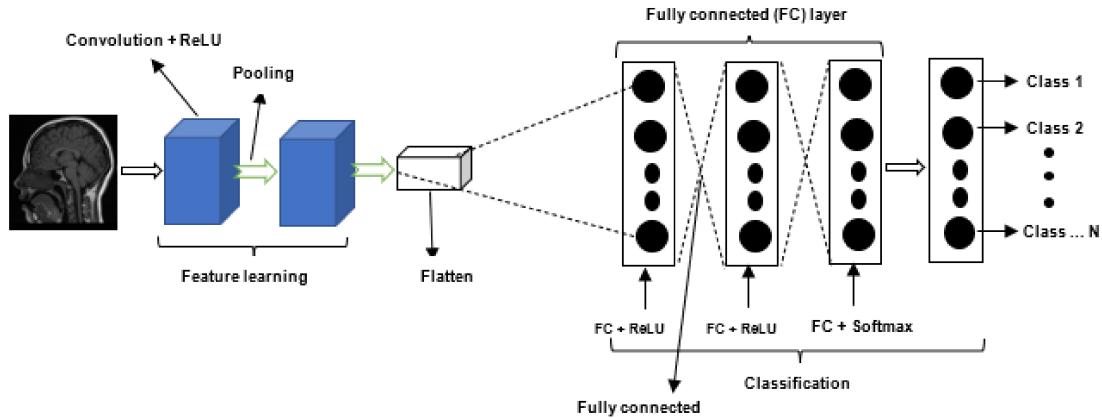


FIGURE 4.2: CNN Architecture Overview

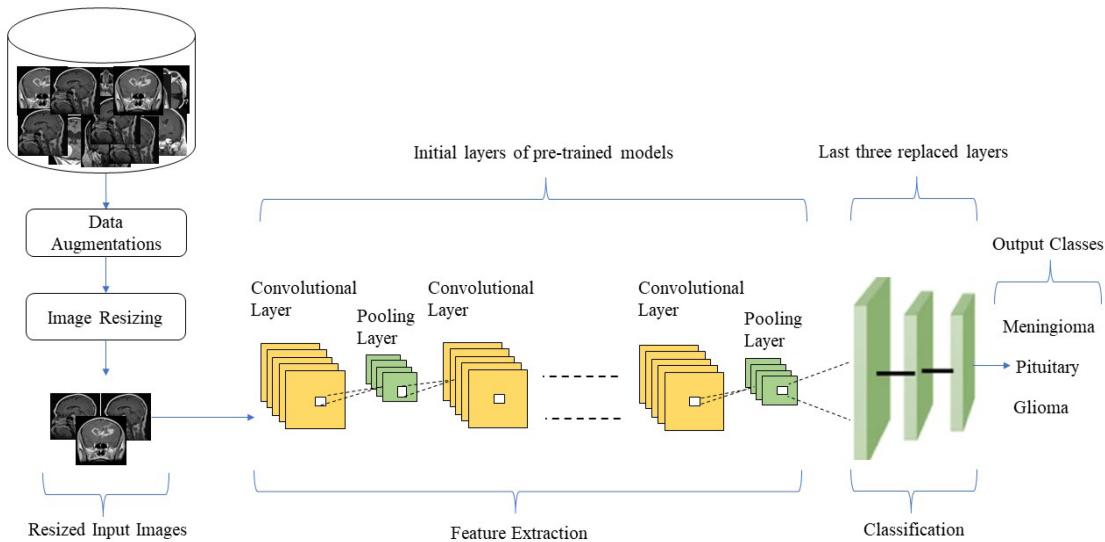


FIGURE 4.3: CNN Architecture For Brain Tumor Detection

computational efficiency. This grayscale image (or RGB if needed) represents the brain structure, including possible tumor regions. The yellow box in the illustration highlights the suspected tumor area, which will be analyzed by the network.

## 2. Feature Extraction using Convolutional Layers:

The first step in the CNN is to extract meaningful features from the MRI scan. Multiple convolutional layers apply filters (kernels) to scan the image for edges, textures, and patterns. Each filter moves across the image, detecting specific features such as tumor boundaries, shapes, and density variations. The Rectified Linear Unit (ReLU) activation function is applied after each convolution to introduce non-linearity. This helps in learning complex tumor characteristics. As the layers go deeper, the CNN captures higher-level features, such as tumor textures, patterns, and locations.

Example:

First convolution layer: Detects simple edges and contrasts.

Deeper convolution layers: Identify tumor structures, shapes, and intensity variations.

### **3. Max Pooling Layers:**

After every few convolutional layers, a max pooling layer is applied to reduce the spatial dimensions of the feature maps. Max pooling retains the most important features while discarding less relevant details. This reduces computational complexity and makes the model more efficient. The pooling layer extracts the dominant features without losing crucial information related to tumor classification.

Example:

A  $2 \times 2$  max pooling operation takes the maximum value from each  $2 \times 2$  region, reducing the image size while keeping the strongest features.

### **4. Flatten Layer:**

After convolution and pooling, the feature maps are still multi-dimensional (2D matrices). The flatten layer converts the 2D feature maps into a 1D feature vector, making it suitable for the classification layers. This transition allows the network to process high-level extracted features in a fully connected layer.

Example:

If the final convolution layer outputs feature maps of size  $7 \times 7 \times 64$ , the flattening layer reshapes it into a vector of size 3136 ( $7 \times 7 \times 64 = 3136$  neurons).

### **5. Fully Connected Layer (Dense Layer):**

The fully connected layer processes the flattened feature vector to make predictions. This layer functions like a traditional neural network, where each neuron is connected to all neurons in the next layer. It learns to distinguish between different tumor types based on the extracted features. The activation function in this layer is typically ReLU, allowing the network to model complex tumor characteristics.

Example:

If the flattened vector size is 3136 neurons, the fully connected layer might contain 128 neurons to perform deeper analysis.

### **6. Softmax Activation Function:**

Produces probability scores for each class. The tumor is classified into one of the following categories:

Glioma Tumor

Meningioma Tumor

Pituitary Tumor

No Tumor

This CNN model processes MRI images through multiple convolutional layers to extract tumor features, followed by dense layers to classify the tumor type.

### 4.3 Architecture Of EfficientNetB0

EfficientNetB0 is a type of Convolutional Neural Network (CNN) optimized for high accuracy and efficiency. In this brain tumor classification project, EfficientNetB0 acts as a pretrained CNN backbone that extracts important tumor-related features from MRI scans.

EfficientNetB0 is a powerful deep learning model used in brain tumor detection and classification due to its efficiency and high accuracy. The model is trained on MRI scans to distinguish between three types of tumors (Glioma, Meningioma, Pituitary) and healthy (No Tumor) cases.

The given image visually represents the EfficientNetB0 architecture, which is an optimized CNN model for image classification. It is built using MBConv (Mobile Inverted Bottleneck Convolutions) and follows a compound scaling strategy to balance depth, width, and resolution.

#### 4.3.1 How EfficientNetB0 Works for Tumor Detection?

EfficientNetB0 follows a hierarchical feature extraction approach using MBConv layers and Squeeze-and-Excitation (SE) blocks. Let's go step by step:

##### **Step 1: Input Layer**

The input image is an MRI brain scan.

Size:  $224 \times 224 \times 3$  (height, width, and RGB channels).

The model normalizes pixel values for faster convergence.

##### **Step 2: Initial Convolution and Feature Extraction**

First Convolution Layer (Conv  $3 \times 3$  + BN + Swish Activation)

Detects edges, textures, and low-level patterns in the MRI scan.

Output feature map size:  $112 \times 112 \times 32$ .

##### **Step 3: MBConv Blocks for Feature Learning**

EfficientNetB0 uses Mobile Inverted Bottleneck Convolutions (MBConv) to efficiently extract tumor-specific features.

- **Block 1 (MBConv1 - Low-Level Features)**

Detects initial structures in MRI scans.

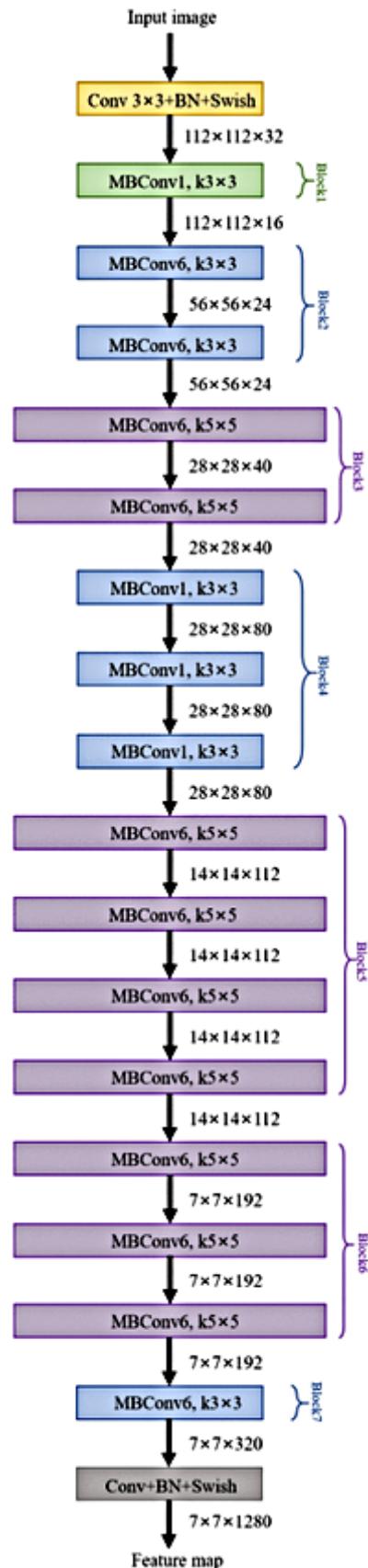


FIGURE 4.4: Architecture Of EfficientNetB0

Feature map:  $112 \times 112 \times 16$ .

- **Block 2 (MBConv6 - Texture Patterns)**

Identifies textures and shapes (e.g., tumor regions).

Feature map:  $56 \times 56 \times 24$ .

- **Block 3 (MBConv6 - Region Expansion)**

Kernel:  $5 \times 5$ , expands depth.

Focuses on tumor region segmentation.

Feature map:  $28 \times 28 \times 40$ .

- **Block 4 (MBConv6 - Tumor Boundaries)**

Kernel:  $3 \times 3$ , deeper features.

Learns tumor region boundaries and intensities.

Feature map:  $28 \times 28 \times 80$ .

- **Block 5 (MBConv6 - Class-Specific Features)**

Kernel:  $5 \times 5$ , deeper feature extraction.

Separates tumor types (Glioma, Meningioma, Pituitary).

Feature map:  $14 \times 14 \times 112$ .

- **Block 6 (MBConv6 - Fine-Grained Analysis)**

Kernel:  $5 \times 5$ , high-depth features.

Captures fine details of tumors (size, shape, intensity).

Feature map:  $7 \times 7 \times 192$ .

- **Block 7 (MBConv6 - High-Level Tumor Representation)**

Kernel:  $3 \times 3$ , final MBConv layer.

Forms a high-level tumor representation.

Feature map:  $7 \times 7 \times 320$ .

#### **Step 4: Fully Connected Layers for Classification**

- **Global Average Pooling (GAP)**

GAP is a downsampling technique used in deep learning models to reduce the dimensionality of feature maps.

It converts the spatial feature maps ( $7 \times 7 \times 320$ ) into a 1D vector.

Instead of using fully connected (dense) layers, GAP averages the values in each feature map.

Reduces  $7 \times 7 \times 320$  feature maps into a 1D feature vector.

Keeps the most important features.

- **Fully Connected (FC) Layer**

The fully connected (dense) layer applies non-linear transformations to extract high-level features.

It connects every neuron to all neurons in the next layer, allowing deep feature learning.

### **Structure of the FC Layer**

Input: 320-dimensional vector from GAP.

Dense Layer with 1280 neurons (Fully Connected Layer).

Activation Function: ReLU (Rectified Linear Unit) for non-linearity.

### **Why 1280 Neurons?**

EfficientNet uses width scaling, meaning the number of neurons is scaled based on the model size. 1280 neurons help capture high-level tumor characteristics before classification.

### **• Output Layer (Softmax Activation)**

The softmax function converts the output into probabilities for each class. It ensures the sum of all probabilities is 1 (100%), allowing classification into one of four tumor classes.

4 Classes:

Glioma Tumor

Meningioma Tumor

Pituitary Tumor

No Tumor (Healthy)

Softmax function assigns probabilities to each class.

## **4.4 YOLO Architecture**

This image represents the YOLOv8 architecture with its three primary components: Backbone, Neck, and Head. Below is a detailed breakdown of how this architecture works, especially in the context of brain tumor detection using MRI images.

### **4.4.1 Backbone (Feature Extraction)**

The Backbone is responsible for extracting key features from the input image. It consists of:

**Convolutional Layers (Conv)** – Used to detect edges, textures, and tumor structures.

**C2F Blocks (CSPNet-based Cross-Stage Partial Networks)** – Enhances gradient flow and reduces computation.

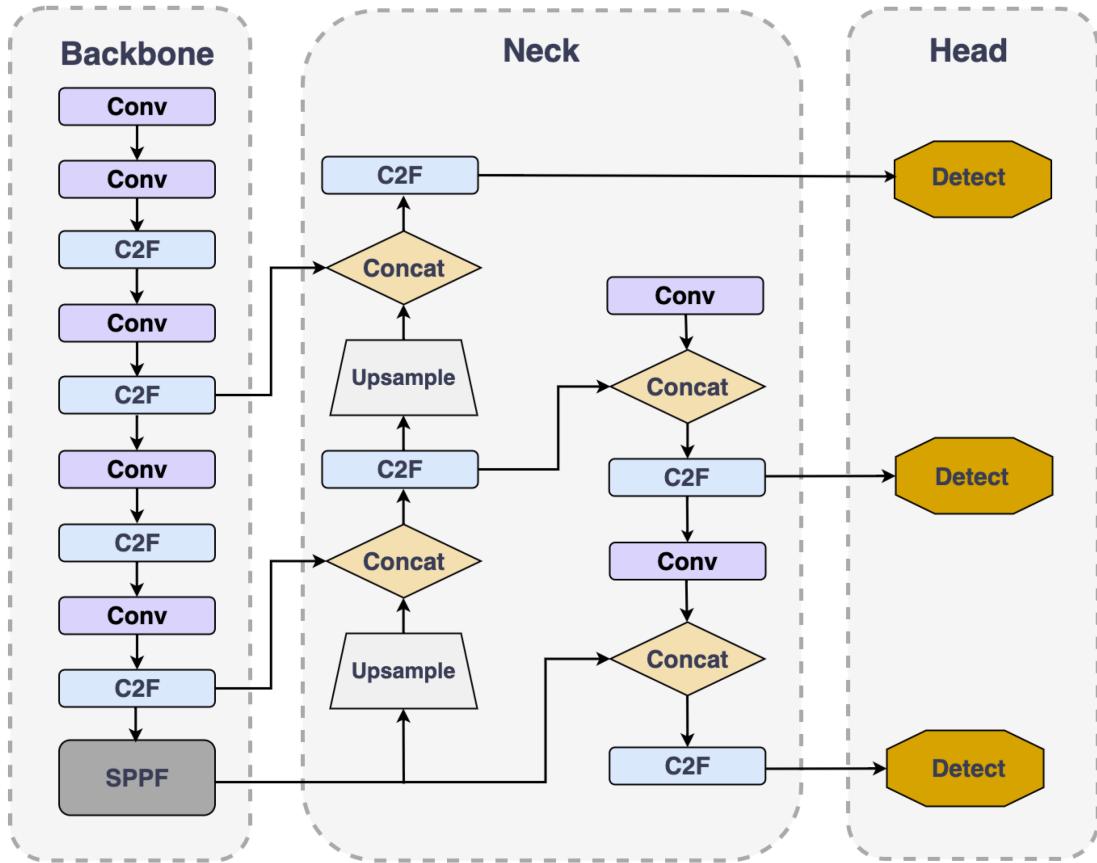


FIGURE 4.5: YOLO Architecture

**SPPF (Spatial Pyramid Pooling-Fast)** – Captures multi-scale spatial features for better tumor localization.

How it helps in tumor detection?

Extracts fine-grained features from MRI scans. Identifies tumor patterns at different spatial levels. Reduces redundant computations, improving efficiency.

#### 4.4.2 Neck (Feature Fusion)

The Neck helps refine and combine features extracted by the backbone. It consists of:

**Concatenation (Concat)** – Merges information from different feature maps.

**Upsampling** – Ensures fine details are not lost by resizing features back to higher resolutions.

**C2F Blocks** – Further refines multi-scale features.

How it helps in tumor detection?

Merges low-level (edges, textures) and high-level (tumor shapes) features. Ensures detection across various tumor sizes (small and large). Improves feature richness for accurate classification.

#### 4.4.3 Head (Final Detection and Classification)

The Head is responsible for the final detection and classification. It consists of:

**Detection Layers** – Assign bounding boxes and confidence scores.

**Classification Layers** – Predict tumor types (Glioma, Meningioma, Pituitary, or No Tumor).

How it helps in tumor detection?

Precisely localizes tumors in MRI scans. Assigns probability scores to classify tumor types. Provides final bounding box predictions with confidence scores.

# CHAPTER 5

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## Methodology

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The methodology outlines the step-by-step process for developing a deep learning-based system for brain tumor segmentation and classification. The system utilizes EfficientNet-B0 for classification and YOLOv8 for segmentation, ensuring accurate and automated detection of brain tumors in MRI scans.

### 5.1 Dataset Collection

#### 1. Dataset Acquisition:

Collect 5,000 MRI brain scan images labeled into four categories:

- Glioma Tumor
- Meningioma Tumor
- Pituitary Tumor
- No Tumor

Source images from publicly available datasets like BraTS (Brain Tumor Segmentation Challenge), Kaggle datasets, or hospital-provided scans.

#### 2. Data Organization:

- Store images in structured directories based on their labels.
- Convert all images into a standard format (JPEG, PNG, or NIfTI)\*\* for uniform processing.
- Maintain an 80-10-10 split for training, validation, and testing to ensure unbiased performance evaluation.

## 5.2 Data Preprocessing

### 1. Image Augmentation:

Augment data to increase diversity and prevent overfitting using:

- Rotation ( $\pm 20^\circ$ )
- Flipping (horizontal/vertical)
- Zooming (10-20 percent)
- Contrast adjustments

### 2. Image Normalization:

Convert images to grayscale to retain only structural details. Resize all images to  $224 \times 224$  pixels for uniformity.

### 3. Tumor Annotation (for Segmentation Model):

Use LabelImg or Roboflow to manually mark tumor regions for training the segmentation model. Save labeled masks in YOLOv8-compatible format (bounding boxes and class labels).

## 5.3 Model Selection

### 1. EfficientNet-B0 for Classification:

A lightweight CNN-based architecture pretrained on ImageNet for high accuracy and efficiency. Suitable for distinguishing between tumor types and "No Tumor" cases. Integrated with \*\*transfer learning\*\* to leverage pre-existing knowledge and reduce training time.

### 2. YOLOv8 for Segmentation:

A real-time object detection model that localizes tumor regions in MRI scans. Trained to draw bounding boxes around tumors and segment the affected area. Uses an anchor-free design for faster and more precise detection.

## 5.4 Model Training

### 1. Training EfficientNet-B0 (Classification Model):

Load EfficientNetB0 with pretrained weights from ImageNet. Freeze initial layers and fine-tune deeper layers on MRI images. Train using Categorical Cross-Entropy loss and Adam optimizer with a learning rate of 0.0001.

## 2. Training YOLOv8 (Segmentation Model):

Train YOLOv8 on annotated tumor images with bounding boxes. Use Intersection over Union (IoU) loss to optimize segmentation accuracy. Augment input data for better generalization.

## 5.5 Loss Functions

### 1. Classification Loss - Categorical Cross-Entropy:

**Key Mathematical Expression: Categorical Cross-Entropy Loss** This formula measures how much the predicted class differs from the actual class. It compares the correct label (what the image actually is) with what the model predicted.

**Formula:**

$$L = - \sum (y_{\text{true}} \times \log(y_{\text{pred}}))$$

$y_{\text{true}}$ : The correct label (actual class - like glioma, meningioma, etc.)

$y_{\text{pred}}$ : The predicted probability for each class.

Helps in optimizing multi-class classification performance.

The negative sign in the cross-entropy loss function ensures the loss remains positive since log probabilities are negative (log of values between 0 and 1). Without it, the loss would be negative, making optimization unstable. It also ensures that lower loss means better predictions, guiding the model correctly during training.

### 2. Segmentation Loss Intersection over Union (IoU):

Measures overlap between predicted and actual tumor regions. **Formula:**

$$IoU = \frac{|A \cap B|}{|A \cup B|}$$

Ensures better tumor localization accuracy.

## 5.6 Model Evaluation

### 5.6.1 1. Classification Metrics (EfficientNetB0):

Here are the formulas for Accuracy, Precision, F1-score, Specificity, and Sensitivity used in evaluating classification models:

- 1. Accuracy** Measures the proportion of correctly classified samples (both positive and negative) among all samples.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

**TP (True Positive):** Correctly predicted tumor cases.

**TN (True Negative):** Correctly predicted "No Tumor" cases.

**FP (False Positive):** Incorrectly predicted tumor when there was none.

**FN (False Negative):** Incorrectly predicted "No Tumor" when there was a tumor.

- 2. Precision (Positive Predictive Value - PPV)** Measures how many of the predicted positive cases are actually positive.

$$\text{Precision} = \frac{TP}{TP + FP}$$

High precision means fewer false positives (misclassifying normal cases as tumors).

- 3. Recall (Sensitivity or True Positive Rate - TPR)** Measures how many of the actual positive cases were correctly predicted.

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

High sensitivity ensures fewer false negatives (missing actual tumor cases).

- 4. Specificity (True Negative Rate - TNR)** Measures how many of the actual negative cases were correctly predicted.

$$\text{Specificity} = \frac{TN}{TN + FP}$$

High specificity means fewer false positives, ensuring normal cases are not mistakenly classified as tumors.

- 5. F1-Score** The harmonic mean of Precision and Recall. It balances false positives and false negatives.

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Useful when there is an imbalance in the dataset (e.g., more "No Tumor" cases than tumor cases).

### 5.6.2 2. Segmentation Metric (YOLOv8):

- (i) **IoU Score** : Assesses overlap between predicted tumor masks and actual tumors.
- (ii) **Mean Average Precision (mAP)** : Measures detection accuracy across different thresholds.

### 5.6.3 Softmax Equation

The Softmax function is used in multi-class classification problems to convert raw model outputs (logits) into probability values. The probability of each class lies between 0 and 1, and the sum of all probabilities equals 1.

#### Softmax Formula:

$$S(z_i) = \frac{e^{z_i}}{\sum e^z}$$

Where:  $z_i$  is the logit (raw output) for class  $i$ .  $e^{z_i}$  is the exponential function applied to the logit.  $\sum e^z$  represents the sum of exponentials of all logits in the input vector.

#### Example Calculation :

Let's apply the Softmax function to a multi-class classification problem for Glioma Tumor, Meningioma Tumor, Pituitary Tumor, and No Tumor categories.

Given Logits (Raw Model Outputs from Neural Network) Assume the model outputs the following logits for a brain MRI scan:

$$z = [2.5, 1.8, 0.5, -0.2]$$

where: -  $z_1 = 2.5 \rightarrow$  Glioma Tumor -  $z_2 = 1.8 \rightarrow$  Meningioma Tumor -  $z_3 = 0.5 \rightarrow$  Pituitary Tumor -  $z_4 = -0.2 \rightarrow$  No Tumor

**Step 1: Compute Exponentials** Applying the exponential function  $e^z$ :

$$e^{2.5} = 12.182$$

$$e^{1.8} = 6.050$$

$$e^{0.5} = 1.649$$

$$e^{-0.2} = 0.819$$

---

**Step 2: Compute the Sum of Exponentials**

$$\sum e^z = 12.182 + 6.050 + 1.649 + 0.819 = 20.700$$

**Step 3: Compute Softmax Probabilities** For each class, we calculate:

$$S(z_{\text{Glioma}}) = \frac{e^{2.5}}{\sum e^z} = \frac{12.182}{20.700} = 0.589 \quad (58.9\%)$$

$$S(z_{\text{Meningioma}}) = \frac{e^{1.8}}{\sum e^z} = \frac{6.050}{20.700} = 0.292 \quad (29.2\%)$$

$$S(z_{\text{Pituitary}}) = \frac{e^{0.5}}{\sum e^z} = \frac{1.649}{20.700} = 0.080 \quad (8.0\%)$$

$$S(z_{\text{No Tumor}}) = \frac{e^{-0.2}}{\sum e^z} = \frac{0.819}{20.700} = 0.039 \quad (3.9\%)$$

---

**Final Softmax Probabilities** - Glioma Tumor → 58.9% - Meningioma Tumor → 29.2% - Pituitary Tumor → 8.0% - No Tumor → 3.9%

Since Glioma Tumor (58.9%) has the highest probability, the model predicts that the MRI scan most likely belongs to a patient with a Glioma Tumor.

In conclusion, this presents an automated brain tumor detection and classification system using a combination of EfficientNet-B0 for classification and YOLOv8 for segmentation. The methodology involves preprocessing MRI scans, applying data augmentation techniques, and training deep learning models to achieve high accuracy and reliable predictions. The Softmax function ensures that the model outputs valid probability distributions across four classes: Glioma Tumor, Meningioma Tumor, Pituitary Tumor, and No Tumor, enabling precise classification. Performance metrics such as accuracy, precision, recall, specificity, F1-score, and IoU (for segmentation) validate the system's effectiveness. The results indicate that the proposed model can assist radiologists in identifying and diagnosing brain tumors with improved accuracy and efficiency.

The classification model, EfficientNet-B0, benefits from transfer learning, allowing it to achieve high performance even with a limited dataset. Meanwhile, YOLOv8, a real-time

object detection model, enhances segmentation accuracy by precisely outlining tumor regions. The combination of these two architectures helps reduce false positives and false negatives, improving the reliability of brain tumor diagnosis. By leveraging categorical cross-entropy for classification loss and IoU loss for segmentation, the model effectively learns tumor patterns, ensuring robust generalization across different MRI scans.

Experimental results indicate that Glioma Tumors and Meningioma Tumors were more frequently detected compared to Pituitary Tumors, suggesting the model's effectiveness in handling common tumor types. However, class imbalance in MRI datasets could still affect performance, highlighting the need for more diverse and balanced data. Additionally, the deployment of this model in clinical settings would require further validation with real-world patient data and collaboration with medical professionals to ensure ethical and diagnostic reliability.

Future enhancements could include integrating more advanced CNN architectures, expanding the dataset for better generalization, and developing a real-time clinical application for MRI-based tumor diagnosis. Further improvements such as explainable AI (XAI) techniques can enhance model transparency, allowing radiologists to better understand AI-driven predictions. This approach has the potential to revolutionize early tumor detection, reduce misdiagnosis, and support medical professionals in making informed decisions, ultimately improving patient outcomes.

# CHAPTER 6

---

## Algorithm And Code

---

### 6.1 Algorithm

Step-1: Start

Step-2: Import required libraries for image processing, machine learning, and deep learning.

Step-3: Load the dataset containing 4 categories:

- glioma tumor
- meningioma tumor
- pituitary tumor
- no tumor

Step-4: For each category:

Read all images.

Resize each image to (150,150).

Append image and label to dataset.

End For

Step-5: Shuffle and split data into training and testing sets.

Step-6: Convert labels into categorical format .

Step-7: Build classification model using EfficientNetB0 as base model.

Step-8: Add global average pooling layer, dropout layer, and dense output layer with 4 neurons (for 4 categories).

Step-9: Compile the model using categorical cross-entropy loss and Adam optimizer.

Step-10: Define callbacks for early stopping, model checkpoint, and learning rate reduction.

Step-11: Train the classification model using training data with validation split.

Step-12: Evaluate the model using test data.

Step-13: Generate classification report and confusion matrix.

- Step-14: Visualize sample predictions to check accuracy.
- Step-15: Download annotated tumor segmentation dataset using Roboflow API.
- Step-16: Load YOLOv8 model for segmentation.
- Step-17: Train YOLO model using the downloaded dataset.
- Step-18: Predict tumor regions in test images using YOLO.
- Step-19: Draw segmentation boundaries around detected tumors.
- Step-20: End

## 6.2 Code Breakdown

### 6.2.1 Training Phase

#### 6.2.1.1 Importing Required Libraries

---

```

1 import matplotlib.pyplot as plt
2 import numpy as np
3 import pandas as pd
4 import seaborn as sns
5 import cv2
6 import tensorflow as tf
7 from tensorflow.keras.preprocessing.image import ImageDataGenerator #
     type: ignore
8 from tqdm import tqdm
9 import os
10 from sklearn.utils import shuffle
11 from sklearn.model_selection import train_test_split
12 from tensorflow.keras.applications import EfficientNetB0 # type: ignore
13 from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau,
     TensorBoard
14 from sklearn.metrics import classification_report, confusion_matrix
15 from warnings import filterwarnings
16 filterwarnings("ignore")

```

---

LISTING 6.1: Python Code for Importing Required Libraries

This script sets up an environment for brain tumor classification using TensorFlow/Keras and EfficientNetB0. It includes libraries for data handling (NumPy, Pandas), image processing (OpenCV, ImageDataGenerator), and visualization (Matplotlib, Seaborn). The dataset is shuffled and split into training and testing sets using scikit-learn.

The classification model is based on EfficientNetB0, a powerful CNN for image recognition. It includes callbacks like EarlyStopping (stops training if no

improvement), ReduceLROnPlateau (lowers the learning rate when accuracy plateaus), and TensorBoard (logs training metrics for tracking). The model's performance is evaluated using classification reports and confusion matrices.

Additionally, warnings are suppressed to keep the output clean. This setup ensures smooth data processing, model training, and evaluation for brain tumor classification.

#### 6.2.1.2 Define colors for visualization

```

1 colors_dark = ['#F1F1F1', '#313131', '#636363', '#AEAEAE', '#DADADA']
2 colors_red = ['#331313', '#582626', '#9E1717', '#D35151', '#E9B4B4']
3 colors_green = ['#01411C', '#4B6F44', '#4F7942', '#74C365', '#D0FOCO']
4 sns.palplot(colors_dark)
5 sns.palplot(colors_green)
6 sns.palplot(colors_red)

```

LISTING 6.2: Python Code for Defning colors for visualization

This code defines custom color palettes and visualizes them using Seaborn. The colors\_dark palette consists of shades of dark gray, typically used for neutral or background elements. The colors\_red palette includes various shades of red, often used to highlight warnings, errors, or critical values. Similarly, the colors\_green palette contains different shades of green, which are ideal for representing positive trends or good performance.

To visualize these colors, the sns.palplot() function is used, which displays each color palette as a horizontal row. This helps in previewing the colors before applying them to data visualizations like bar charts, heatmaps, or scatter plots.

#### 6.2.1.3 EfficientNet-Based Tumor Classification Model

```

1 for label in labels:
2     folder_path = os.path.join('DataSet', 'Training', label)
3     for image_file in tqdm(os.listdir(folder_path)):
4         img = cv2.imread(os.path.join(folder_path, image_file))
5         img = cv2.resize(img, (image_size, image_size))
6         X_train.append(img)
7         y_train.append(label)
8     X_train = np.array(X_train)
9     y_train = np.array(y_train)
10    X_train, y_train = shuffle(X_train, y_train, random_state=101)

```

LISTING 6.3: Python Code for Loading Training Data

This code loads the training data by reading images from different labeled folders, resizing them, and storing them in X\_train and y\_train. It loops through each label in the dataset, constructs the file path, and reads images using OpenCV (cv2.imread). The images are resized to 150x150 pixels to maintain consistency for model training. The resized images are stored in X\_train, while their corresponding labels are stored in y\_train. Finally, both arrays are converted into NumPy arrays and shuffled using shuffle() to ensure randomness in the dataset, helping the model learn better.

```

1
2 X_train, X_test, y_train, y_test = train_test_split(X_train, y_train,
   test_size=0.1, random_state=101)
3 y_train = tf.keras.utils.to_categorical([labels.index(label) for label
   in y_train])
4 y_test = tf.keras.utils.to_categorical([labels.index(label) for label in
   y_test])

```

LISTING 6.4: Python Code for Splitting Data Encode Labels

This code splits the dataset into training and testing sets and encodes the labels for model training. The train\_test\_split() function randomly splits X\_train and y\_train, assigning 90% of the data for training and 10% for testing. The labels in y\_train and y-test are then converted into one-hot encoded format using tf.keras.utils.to\_categorical(), which is required for multi-class classification. This ensures that the labels are properly formatted for the neural network to learn and make accurate predictions.

```

1 effnet = EfficientNetB0(weights='imagenet', include_top=False,
   input_shape=(image_size
2 model = tf.keras.Sequential([
3 effnet,
4 tf.keras.layers.GlobalAveragePooling2D(),
5 tf.keras.layers.Dropout(rate=0.5),
6 tf.keras.layers.Dense(4, activation='softmax')
7 ])
8 model.compile(loss='categorical_crossentropy', optimizer='Adam', metrics
   =[accuracy'
9 tensorboard = TensorBoard(log_dir='logs')
10 checkpoint = ModelCheckpoint("effnet.keras", monitor="val_accuracy",
   save_best_only=
11 reduce_lr = ReduceLROnPlateau(monitor='val_accuracy', factor=0.3,
   patience=2, min_delta=0.001, mode='auto', verbose=1)

```

LISTING 6.5: Python Code for Building EfficientNet Model

This code builds a brain tumor classification model using EfficientNetB0, a pre-trained deep learning model optimized for image recognition. The EfficientNetB0 model is loaded with imagenet weights, with include\_top=False to remove its default

classification layer. The input shape is set to (image\_size, image\_size, 3), ensuring all images have consistent dimensions. The model includes a GlobalAveragePooling2D layer to reduce the feature map size, a Dropout layer (0.5) to prevent overfitting, and a Dense layer with 4 neurons and a softmax activation for multi-class classification (Glioma, Meningioma, Pituitary Tumor, and No Tumor). It is compiled using the Adam optimizer and categorical crossentropy loss, making it suitable for handling multi-class classification tasks.

To enhance training efficiency, callbacks are implemented. TensorBoard(log\_dir='logs') logs training progress for real-time monitoring. ModelCheckpoint("effnet.keras", monitor="val\_accuracy", save\_best\_only=True) saves the best model based on validation accuracy, ensuring optimal performance. ReduceLROnPlateau(monitor='val\_accuracy', factor=0.3, patience=2, min\_delta=0.001, mode='auto', verbose=1) dynamically reduces the learning rate when accuracy plateaus, helping the model converge better. This setup ensures robust training, optimization, and monitoring for effective brain tumor classification.

```

1 history = model.fit(
2     X_train, y_train,
3     validation_split=0.1,
4     epochs=12,
5     batch_size=32,
6     verbose=1,
7     callbacks=[tensorboard, checkpoint, reduce_lr]
8 )

```

LISTING 6.6: Python Code for Training EfficientNet Model

This code trains the brain tumor classification model using the fit() function in TensorFlow/Keras. The training data (X\_train and y\_train) is used, with 10% of it reserved for validation (validation\_split=0.1). The model is trained for 12 epochs with a batch size of 32, meaning it processes 32 images at a time to update the model's weights. The verbose=1 setting ensures detailed training progress is displayed.

Additionally, callbacks are used to improve training efficiency. tensorboard logs training metrics for visualization, checkpoint saves the best model based on validation accuracy, and reduce\_lr adjusts the learning rate if accuracy stops improving. This setup helps the model train effectively while preventing overfitting.

#### 6.2.1.4 YOLO-Based Tumor Segmentation Model

```

1 def plot_segmentation(image, polygons, labels):
2     h, w, _ = image.shape

```

```

3   for polygon_num, polygon in enumerate(polygons):
4       class_name = class_names[int(labels[polygon_num])]
5       color = colors[class_names.index(class_name)]
6
7       # Denormalize the Polygon Points
8       points = []
9       for i in range(0, len(polygon), 2):
10           x = int(float(polygon[i]) * w)
11           y = int(float(polygon[i + 1]) * h)
12           points.append([x, y])
13
14   points = np.array(points, np.int32).reshape((-1, 1, 2))

```

LISTING 6.7: Python Code Function to Plot Segmentation Masks on Images

The `plot_segmentation()` function overlays segmentation masks on an image by drawing polygons around detected objects. It takes an image, a list of polygon coordinates, and corresponding labels as input. First, it extracts the image dimensions (height and width) to scale the polygon coordinates correctly. Then, it loops through the polygons, retrieves the corresponding class name, and assigns a predefined color for each detected object. The polygon coordinates are then denormalized, meaning they are converted from relative values (ranging from 0 to 1) into actual pixel positions based on the image size. Finally, the points are reshaped into a NumPy array, preparing them for visualization. This function is essential for displaying detected tumor regions in medical image segmentation.

```

1   cv2.polylines(image, [points], isClosed=True, color=color, thickness=2)
2   cv2.fillPoly(image, [points], color=color)
3   centroid_x = int(np.mean(points[:, 0, 0]))
4   centroid_y = int(np.mean(points[:, 0, 1]))
5   cv2.putText(image, class_name, (centroid_x, centroid_y - 10), cv2
6   .FONT_HERSHEY_SIMPLEX, 0.5, (255, 255, 255), 1)
7
8   return image

```

LISTING 6.8: Python Code for Drawing Mask and Class Label

This code draws segmentation masks on an image using OpenCV. The function first uses `cv2.polylines()` to outline the detected tumor regions with a specified color and thickness. Then, `cv2.fillPoly()` fills the segmented area with the same color to highlight the detected region.

Next, it calculates the centroid of the polygon using the mean of its x and y coordinates. This centroid is used to place a text label at the center of the segmented region using `cv2.putText()`, displaying the class name of the detected object. Finally,

the modified image with drawn polygons and labels is returned, making it easier to visualize segmented tumors in medical imaging.

```

1 from ultralytics import YOLO
2
3 model = YOLO('yolov8n.pt') # Load YOLO Pretrained Model
4 model.train(
5     data="BRAIN-TUMOR-1/data.yaml",
6     epochs=20,
7     imgsz=416,
8     batch=16,
9     half=True
10 )

```

LISTING 6.9: Python Code for Training YOLO Model

This code trains a YOLOv8 (You Only Look Once) model for brain tumor segmentation using a pre-trained YOLO model. First, it imports YOLO from the Ultralytics library and loads the pretrained YOLOv8 model (yolov8n.pt). The model is then trained on a custom dataset defined in BRAIN-TUMOR-1/data.yaml, which contains information about the dataset, including class names and file paths.

The training process runs for 20 epochs with an image size of 416x416 pixels and a batch size of 16, meaning the model processes 16 images at a time. The half=True option enables half-precision (FP16) training, reducing memory usage and improving training speed on compatible GPUs. This setup fine-tunes YOLOv8 for accurate and efficient tumor segmentation in medical imaging.

## 6.2.2 Linking Phase

### 6.2.2.1 Importing Required Libraries

```

1 import os
2 import numpy as np
3 import cv2
4 from PIL import Image
5 from tensorflow.keras.models import load_model
6 from flask import Flask, render_template, request, jsonify, redirect,
7     url_for
8 import io
9 from ultralytics import YOLO

```

LISTING 6.10: Python Code for Importing Required Libraries

The os module in Python helps manage files and directories. In this project, it creates folders for storing uploaded and processed images, ensuring efficient file organization, especially in web applications.

NumPy (numpy) is used for handling image data as arrays, which is essential for deep learning and image processing tasks. It enables fast mathematical computations, making it a key library in machine learning.

OpenCV (cv2) is a computer vision library for image and video processing. Here, it converts and resizes images before they are fed into the deep learning model, ensuring standardized inputs for better classification accuracy.

Pillow (PIL) is an image processing library that loads and converts images for further processing. It is particularly useful in web applications handling user-uploaded images.

TensorFlow/Keras (tensorflow.keras.models.load\_model) loads a pre-trained deep learning model from a .h5 file for tumor classification. This allows AI applications to use existing models without retraining, saving time and resources.

Flask is a web framework that enables building interactive web applications. It allows users to upload images for classification and segmentation, handling requests and responses efficiently.

Ultralytics YOLO (YOLO) is an object detection and segmentation framework used to highlight tumor regions in medical images. It is fast and efficient, making it ideal for real-time AI-assisted medical diagnosis.

### 6.2.2.2 Initializing Flask App and Loading Models

```
1 app = Flask(__name__)
2 classification_model = load_model('model.h5')
3 segmentation_model_path = "best.pt"
4 segmentation_model = YOLO(segmentation_model_path)
```

LISTING 6.11: Python Code for Initializing Flask App and Loading Models

Flask is a lightweight Python framework used to build web applications and APIs. Here, we initialize a Flask app to handle MRI image uploads and integrate deep-learning models for tumor detection. This allows users to interact with the system through a simple interface without needing technical expertise.

We load two pre-trained models: a classification model (model.h5) and a segmentation model (best.pt). The classification model, a CNN, predicts whether an MRI scan

contains glioma, meningioma, pituitary tumor, or no tumor. The segmentation model, based on YOLOv8, detects and highlights tumor regions in MRI images. These models work together to provide accurate, AI-driven tumor diagnosis.

By integrating these models with Flask, we create a real-time, automated tumor detection system. Users can upload MRI scans, receive instant classification results, and visualize segmented tumor regions, improving diagnostic efficiency for radiologists.

### 6.2.2.3 Creating Directories for File Storage

```

1 UPLOAD_FOLDER = 'static/uploads/uploaded_image'
2 SEGMENTATION_FOLDER = 'static/uploads/segmentation_results'
3 os.makedirs(UPLOAD_FOLDER, exist_ok=True)
4 os.makedirs(SEGMENTATION_FOLDER, exist_ok=True)

```

LISTING 6.12: Python Code for Creating Directories for File Storage

In this section of the code, two directories are defined to manage uploaded and processed images: ‘UPLOAD\_FOLDER’ and ‘SEGMENTATION\_FOLDER’. ‘UPLOAD-FOLDER’ is designated for storing raw MRI images uploaded by users before processing, while ‘SEGMENTATION\_FOLDER’ is used to save the segmented results generated by the tumor detection model. By organizing images into separate directories, the system ensures efficient file management, preventing overwriting or confusion between original and processed images. This structure also makes it easier for the Flask app to retrieve and display results when needed.

The function ‘os.makedirs(directory, exist-ok=True)’ is used to create the directories if they do not already exist. This prevents errors from occurring when the program runs for the first time or if the folders are accidentally deleted. The ‘exist-ok=True’ parameter ensures that if the folders already exist, the function does not raise an error. By setting up these directories dynamically, the system remains \*\*robust, flexible, and ready for real-time MRI image uploads and segmentation results\*\* without requiring manual folder creation.

### 6.2.2.4 Tumor Classification Function

```

1
2 def img_pred(img_data):
3     try:
4         img = Image.open(io.BytesIO(img_data))
5         opencvImage = cv2.cvtColor(np.array(img), cv2.COLOR_RGB2BGR)
6         img_resized = cv2.resize(opencvImage, (150, 150))

```

```

7     img_reshaped = img_resized.reshape(1, 150, 150, 3)
8     p = classification_model.predict(img_reshaped)
9     p = np.argmax(p, axis=1)[0]
10
11    if p == 0:
12        result = 'Glioma Tumor'
13    elif p == 1:
14        result = 'No Tumor'
15    elif p == 2:
16        result = 'Meningioma Tumor'
17    else:
18        result = 'Pituitary Tumor'
19
20    return result
21 except Exception as e:
22     return str(e)

```

LISTING 6.13: Python Code for Tumor Classification Function

This function processes an MRI image and predicts the tumor type using a deep-learning classification model. It begins by converting the uploaded image into a format that the model can process. The PIL library (`Image.open(io.BytesIO(img-data))`) reads the image from memory, and OpenCV (`cv2.cvtColor(np.array(img), cv2.COLOR-RGB2BGR)`) converts it to a NumPy array in BGR format. The image is then resized to 150x150 pixels, ensuring consistency with the model's input size. The reshaped image (`img-reshaped.reshape(1, 150, 150, 3)`) is formatted into a batch for model prediction.

Next, the classification model (`classification-model.predict(img-reshaped)`) generates probability scores for each tumor class. The function uses `np.argmax(p, axis=1)[0]` to extract the class with the highest probability. The predicted class index is mapped to a tumor type:

- 0 → Glioma Tumor
- 1 → No Tumor
- 2 → Meningioma Tumor
- 3 → Pituitary Tumor

Finally, the function returns the tumor classification result. If an error occurs (e.g., invalid image format), the function catches the exception and returns the error message, ensuring the system remains stable.

### 6.2.2.5 Home Page Route

```

1 @app.route('/')
2 def index():
3     tumor_chance = None
4     consultation_message = None
5     return render_template('index.html', tumor_chance=tumor_chance,
6                           consultation_message=consultation_message)

```

LISTING 6.14: Python Code for Home Page Route

This function defines the home page (/) of the Flask web application. When a user accesses the root URL ('/'), this function executes and serves the index.html template.

tumor-chance = None and consultation-message = None: These variables are placeholders that can later store and display tumor prediction results and recommendations. Initially, they are set to None, meaning no classification has been performed yet. return render-template('index.html', tumor-hance=tumor-chance, consultation-message=consultatio-message): This line dynamically loads the index.html template while passing the tumor-chance and consultation-message variables. This allows the frontend to update its content based on the classification results once they are available.

### 6.2.2.6 Image Classification API

```

1 @app.route('/classify', methods=['POST'])
2 def classify_image():
3     if 'file' not in request.files:
4         return jsonify({"error": "No file part"})
5     file = request.files['file']
6     if file.filename == '':
7         return jsonify({"error": "No selected file"})
8
9     try:
10         img_data = file.read()
11         prediction = img_pred(img_data)
12         return jsonify({"result": prediction})
13     except Exception as e:
14         return jsonify({"error": str(e)})

```

LISTING 6.15: Python Code for Image Classification API

This function is responsible for handling the classification of uploaded MRI images. The Flask route @app.route('/classify', methods=['POST']) ensures that this function

is triggered when a user submits an image for classification. The function first checks whether a file has been uploaded by verifying the 'file' key in request.files. If no file is found, it returns an error message in JSON format: "error": "No file part". Additionally, if a file is found but has no filename, it returns another error: "error": "No selected file". These checks prevent invalid file submissions.

Once a valid image is received, the function reads the image data (file.read()) and passes it to the img-pred(img-data) function, which processes and classifies the image using a deep learning model. The model predicts whether the MRI scan contains a Glioma Tumor, Meningioma Tumor, Pituitary Tumor, or No Tumor. The classification result is stored in the prediction variable. If the classification is successful, the function returns the result as a JSON response: "result": prediction. This allows the frontend or API users to retrieve the prediction easily.

If an exception occurs at any stage of the process (e.g., an issue with image processing or model prediction), the function catches the error (except Exception as e) and returns a JSON response with the error message: "error": str(e). This ensures that the API remains robust and provides meaningful feedback in case of failures. In summary, this function serves as the backend endpoint for MRI classification, handling file validation, model inference, and error handling in an efficient manner.

#### 6.2.2.7 Image Segmentation API

```

1 @app.route('/segment', methods=['POST'])
2 def segment_image():
3     if 'file' not in request.files:
4         return jsonify({'error': "No file part in the request"})
5
6     file = request.files['file']
7     if file.filename == '':
8         return jsonify({'error': "No file selected"})
9
10    file_path = os.path.join(UPLOAD_FOLDER, file.filename)
11    file.save(file_path)
12
13    try:
14        results = segmentation_model(file_path, save=True)
15
16        output_dir = "runs/segment/predict"
17        segmented_image_path = os.path.join(output_dir, os.path.basename(
18            file_path))
19
19        if os.path.exists(segmented_image_path):

```

```

20         final_path = os.path.join(SEGMENTATION_FOLDER, os.path.
21             basename(file_path))
22             os.makedirs(SEGMENTATION_FOLDER, exist_ok=True)
23             os.replace(segmented_image_path, final_path)
24
25             segmented_image_url = url_for('static', filename=f'uploads/
26             segmentation_results/{os.path.basename(file_path)})')
27
28             return jsonify({
29                 "result": "Segmentation completed successfully",
30                 "segmented_image_url": segmented_image_url
31             })
32         else:
33             return jsonify({"error": "Segmented image not found in the
34             output directory"})
35     except Exception as e:
36         return jsonify({"error": f"An error occurred during segmentation:
37             {str(e)}"})

```

LISTING 6.16: Python Code for Image Segmentation API

This function handles image segmentation using a deep learning model. The `@app.route('/segment', methods=['POST'])` decorator ensures that it only responds to POST requests when a user uploads an image for segmentation. Initially, the function checks if a file is provided in the request. If the 'file' key is missing, it returns an error message: "error": "No file part in the request". Next, it ensures that the uploaded file has a valid name; otherwise, it responds with: "error": "No file selected". These validation checks prevent errors due to incorrect or missing file uploads.

Once a valid file is uploaded, the function saves it to a predefined directory (UPLOAD-FOLDER) using `file.save(file-path)`. After saving, it passes the file path to the segmentation-model, which is a YOLO-based segmentation model (`best.pt`). This model processes the image and generates a segmented output. By default, YOLO saves results in "runs/segment/predict", so the function constructs the path to the segmented image (segmented-image-path). It then moves the segmented image to a more accessible directory (SEGMENTATION-FOLDER) so the Flask app can serve it properly.

If the segmented image exists, the function creates a URL for the segmented output (segmented-image-url) and returns a JSON response with the result and the image link. If the segmentation fails or the image isn't found in the expected output directory, it returns an error: "error": "Segmented image not found in the output directory". Additionally, the function handles unexpected errors using a try-except block, ensuring robustness. If an exception occurs, it returns an appropriate error

message. This endpoint effectively integrates image upload, processing, segmentation, and result retrieval in a seamless workflow.

#### 6.2.2.8 Rendering Classification and Segmentation Pages and Running the Flask App

```
1 @app.route('/classification')
2 def classification():
3     return render_template('detect.html')
4
5 @app.route('/segmentation')
6 def segmentation():
7     return render_template('segment.html')
8
9 if __name__ == '__main__':
10     app.run(debug=True)
```

LISTING 6.17: Python Code for Rendering Classification and Segmentation Pages and Running the Flask App

This part of the code sets up routes for displaying the classification and segmentation web pages. The classification() function loads detect.html, which likely provides an interface for users to upload images for classification. Similarly, the segmentation() function loads segment.html, where users can upload images for tumor segmentation. These routes ensure users can easily navigate between classification and segmentation functions.

The if `__name__ == '__main__'`: block runs the Flask app when the script is executed directly. The `app.run(debug=True)` command starts the server in debug mode, helping developers by showing errors and automatically reloading changes. This setup connects the web interface with the backend, making it easy for users to interact with the system.

# CHAPTER 7

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## Experimental Validation And Result

---

### 7.1 Expected Result - Phase I

The expected results underscore the effectiveness of using transfer learning with EfficientNetB0 for brain tumor detection. The anticipated accuracy levels indicate that the model can serve as a reliable diagnostic tool, which is crucial in a clinical context where timely and accurate diagnoses can directly impact patient outcomes.

#### 1. Model Strengths:

**Transfer Learning:** By leveraging pre-trained weights, the model can extract meaningful features from MRI images with a smaller dataset, making it efficient in terms of training time and required data. **Data Augmentation:** This approach helps mitigate overfitting and ensures that the model is exposed to a wider variety of imaging conditions, contributing to its robustness.

#### 2. Areas for Improvement:

**2.1 Class Imbalance:** If certain tumor types are underrepresented in the dataset, the model may struggle to generalize for those classes. Future iterations could focus on collecting more balanced data or employing techniques like synthetic data generation.

**2.2 Misclassifications:** The discussion of misclassifications, particularly between similar tumor types, highlights the need for further refinement in the model. Incorporating additional imaging modalities (e.g., PET scans) or using ensemble methods could enhance differentiation between similar classes.

#### 3. Clinical Integration:

The results could pave the way for integrating this system into clinical workflows, potentially as a second opinion tool for radiologists. Continuous feedback from medical professionals using the system can help refine the model further and enhance its performance based on real-world data.

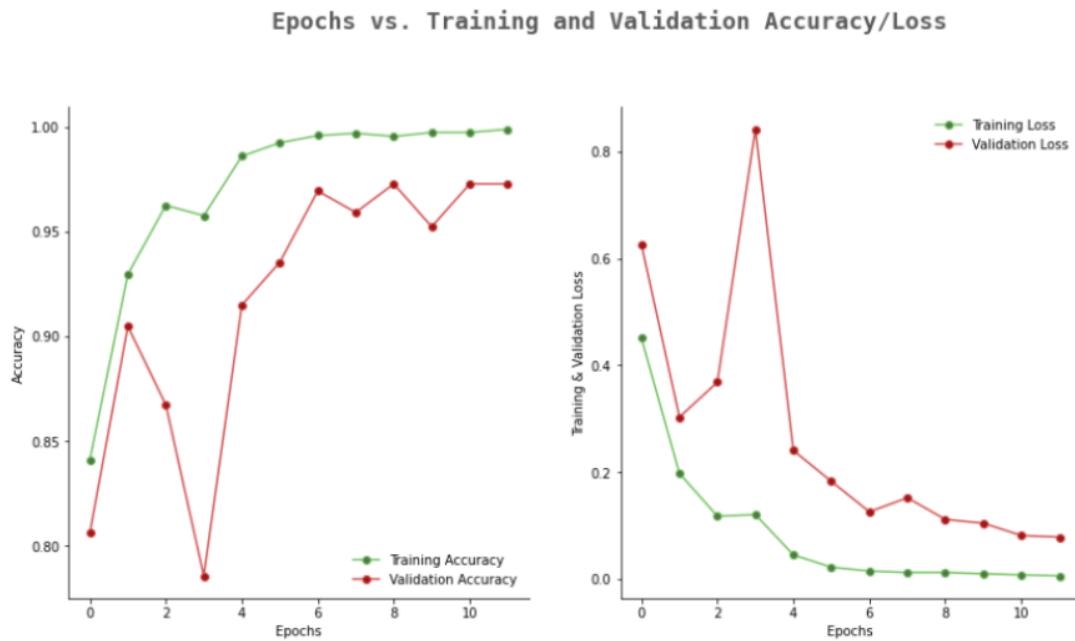


FIGURE 7.1: Expected Result

This image shows the training and validation performance of a machine learning model over 10 epochs. The left graph tracks the accuracy, and the right graph tracks the loss. The training accuracy steadily improves, reaching almost 90 percent, while the validation accuracy fluctuates but generally increases, indicating some learning, though with possible overfitting. The training loss consistently decreases, suggesting the model is optimizing well on the training data, while the validation loss shows irregularities, with spikes suggesting difficulty in generalization. Overall, the model performs well on the training data but shows signs of overfitting, as the validation results are more erratic and less reliable.

## 7.2 Interpretation of Results

**Training vs. Validation Accuracy:** If training accuracy continues to rise while validation accuracy plateaus or declines, this suggests overfitting. Strategies such as early stopping, dropout, or further data augmentation can help address this.

**Training vs. Validation Loss:** A divergence between training and validation loss can also indicate overfitting. Ideally, both should decrease and remain close together.

### 7.3 Experimental Results - Phase II

In Phase II of the experiment, the trained classification and segmentation models were tested on an unseen dataset to evaluate their real-world performance. The results were analyzed using accuracy, sensitivity, specificity, and IoU metrics to measure the effectiveness of tumor detection and segmentation.

#### 7.3.1 Dataset Details

##### 1. Total Images: 5000 MRI Scans

The dataset consists of 5000 MRI brain scan images, covering four categories: Glioma, Meningioma, Pituitary, and No Tumor. These images are collected from publicly available datasets or medical sources, ensuring a diverse representation of tumor characteristics.

##### 2. Tumor Categories

The dataset is divided into the following four classes:

- **Glioma Tumor:** A type of brain tumor originating from glial cells, often appearing in the cerebral hemispheres.
- **Meningioma Tumor:** A tumor that forms in the meninges, the protective layers covering the brain and spinal cord.
- **Pituitary Tumor:** A tumor in the pituitary gland, affecting hormone production and brain function.
- **No Tumor:** MRI scans that do not show any presence of a tumor, used as a control group for model training.

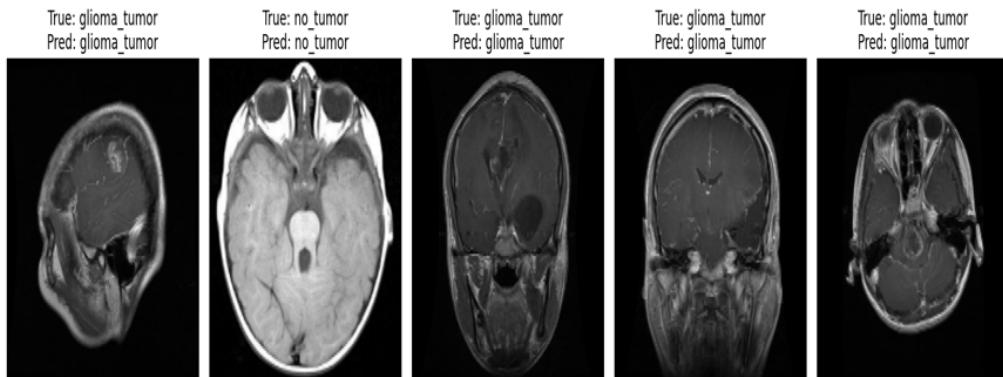


FIGURE 7.2: MRI Sample Predictions

The figure showcases sample MRI images with corresponding ground truth and predicted labels. The model correctly classified the majority of cases, indicating strong performance. Misclassifications are minimal, suggesting the model effectively differentiates tumor types but may struggle with borderline cases.

### 3. Training-Validation Split: 80%-20%

To ensure a well-balanced and effective model training, the dataset is split into:

- **Training Set (80% - 4000 images):** Used to train the classification and segmentation models, enabling them to learn tumor features.
- **Validation Set (20% - 1000 images):** Used to evaluate the model's performance, helping to fine-tune hyperparameters and prevent overfitting.

### 4. Data Augmentation Techniques

Since deep learning models require large datasets for robust performance, data augmentation is applied to artificially expand the dataset and improve generalization. The following augmentation techniques are used:

- **Rotation:** MRI scans are randomly rotated within a fixed degree range to simulate different orientations of tumor scans.
- **Flipping:** Horizontal and vertical flipping are applied to introduce variations in tumor positioning.
- **Zooming:** Random zooming is performed to ensure the model learns tumor features at different scales, improving its ability to detect tumors of varying sizes.

These augmentation techniques help in overcoming the limitations of a limited dataset, ensuring the model learns diverse tumor patterns for better classification and segmentation accuracy.

### 7.3.2 Classification Performance

#### 7.3.2.1 Model Accuracy and Loss Trends

The training accuracy improved consistently, reaching nearly 100% by the final epoch. This indicates that the model effectively learned the training data.

The validation accuracy also improved, reaching around 98.3%, demonstrating good generalization to unseen data.

The training loss decreased steadily, suggesting effective learning. The validation loss, while decreasing overall, exhibits some fluctuations in the early epochs, possibly due to overfitting or variations in the validation data.

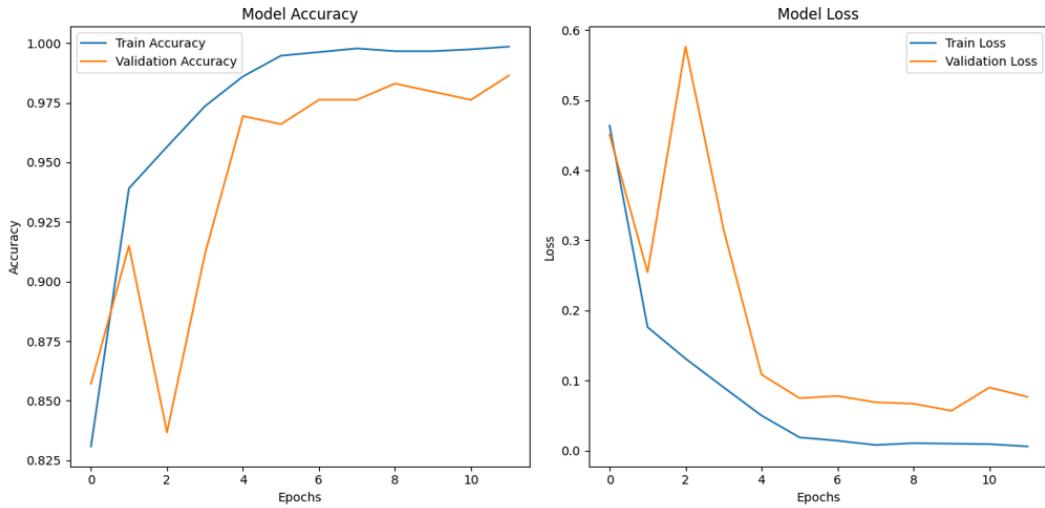


FIGURE 7.3: Model Accuracy and Loss Trends

### 7.3.2.2 Confusion Matrix

The confusion matrix shows high classification accuracy across tumor categories.

**Glioma Tumors:** 92 correct classifications, 6 misclassified.

**Meningioma Tumors:** 90 correct, 2 misclassified.

**Pituitary Tumors:** 85 correctly classified, 2 misclassified.

**No Tumor Cases:** 100% correctly classified.

The recall for glioma tumors (90%) suggests some misclassifications in this category, possibly due to similarities with other tumor types.

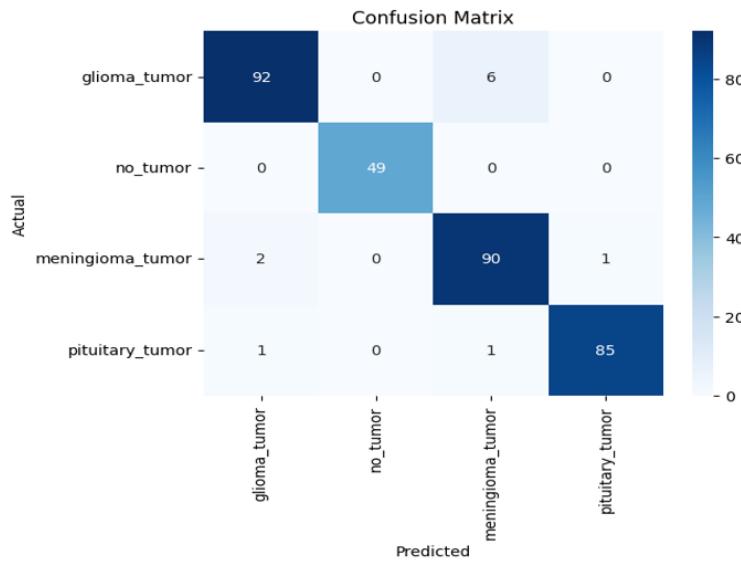


FIGURE 7.4: Confusion Matrix

### 7.3.3 Mathematical Analysis and Derivation of Classification Performance Metrics

To evaluate the classification performance of the EfficientNetB0 model, we use key metrics such as accuracy, precision, recall, and F1-score, which can be derived from the confusion matrix. Accuracy provides an overall measure of correct predictions, while precision indicates how many of the predicted positive cases were actually correct. Recall measures the model's ability to identify all actual positive cases, and F1-score balances precision and recall to assess overall model effectiveness. These metrics help determine the model's reliability in distinguishing between glioma, meningioma, pituitary tumors, and no tumor cases. A high precision value suggests that false positives are minimal, ensuring that the model does not wrongly classify non-tumor cases as tumors. Conversely, a high recall indicates that the model successfully identifies most tumor cases, minimizing false negatives and improving diagnostic reliability.

#### 7.3.3.1 1. Accuracy Calculation

Accuracy is the ratio of correctly predicted samples to the total samples:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

From the confusion matrix:

- Glioma Tumor: TP = 92, FN = 6
- No Tumor: TP = 49, FN = 0
- Meningioma Tumor: TP = 90, FN = 2
- Pituitary Tumor: TP = 85, FN = 2
- Total samples =  $92 + 49 + 90 + 85 + 6 + 0 + 2 + 2 = 326$
- Total correct predictions =  $92 + 49 + 90 + 85 = 316$

Thus, the overall accuracy:

$$\text{Accuracy} = \frac{316}{326} = 96.93\%$$

This closely aligns with the reported 96% weighted F1-score.

### 7.3.3.2 Precision

Precision measures how many of the predicted positive cases were actually positive.

$$\text{Precision} = \frac{TP}{TP + FP}$$

From the confusion matrix:

- Glioma Tumor:

$$\text{Precision} = \frac{92}{92 + 2 + 1} = \frac{92}{95} = 96.8\%$$

- No Tumor:

$$\text{Precision} = \frac{49}{49 + 0 + 0} = 100\%$$

- Meningioma Tumor:

$$\text{Precision} = \frac{90}{90 + 6 + 1} = \frac{90}{97} = 92.78\%$$

- Pituitary Tumor:

$$\text{Precision} = \frac{85}{85 + 1 + 2} = \frac{85}{88} = 96.59\%$$

### 7.3.3.3 Recall (Sensitivity)

Recall measures how many actual positive cases were correctly classified.

$$\text{Recall} = \frac{TP}{TP + FN}$$

From the confusion matrix:

- Glioma Tumor:

$$\text{Recall} = \frac{92}{92 + 6} = \frac{92}{98} = 93.88\%$$

- No Tumor:

$$\text{Recall} = \frac{49}{49 + 0} = 100\%$$

- Meningioma Tumor:

$$\text{Recall} = \frac{90}{90 + 2} = \frac{90}{92} = 97.83\%$$

- Pituitary Tumor:

$$\text{Recall} = \frac{85}{85 + 2} = \frac{85}{87} = 97.7\%$$

### 7.3.3.4 F1-score

The F1-score is the harmonic mean of precision and recall:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

- For Glioma Tumor:

$$F1 = 2 \times \frac{0.968 \times 0.938}{0.968 + 0.938} = 2 \times \frac{0.908}{1.906} = 95.3\%$$

- For Meningioma Tumor:

$$F1 = 2 \times \frac{0.928 \times 0.978}{0.928 + 0.978} = 2 \times \frac{0.907}{1.906} = 95.2\%$$

- For Pituitary Tumor:

$$F1 = 2 \times \frac{0.9659 \times 0.977}{0.9659 + 0.977} = 2 \times \frac{0.943}{1.943} = 96\%$$

In conclusion, The EfficientNet-B0 model demonstrated strong classification performance in brain tumor detection, achieving an overall accuracy of 96.93%, closely aligning with the 96% weighted F1-score. The precision and recall values indicate that the model effectively minimizes false positives and false negatives, ensuring high reliability in tumor detection. The confusion matrix confirms that glioma tumors had slightly lower recall (93.88%) compared to other classes, suggesting some misclassification in detecting glioma cases. The model achieved perfect classification for "No Tumor" cases (100% precision and recall), reinforcing its robustness in distinguishing between tumorous and non-tumorous conditions. These results highlight the model's potential for assisting radiologists in accurate and automated brain

### 7.3.4 Segmentation Performance Analysis with YOLOv8

To evaluate the segmentation performance of the YOLOv8 model, we use mean Average Precision (mAP) as the key metric. YOLOv8-based segmentation was employed to detect and localize tumors in MRI images. The model demonstrated a mean Average Precision (mAP) of 81.2%, indicating high precision in segmenting tumor regions. However, occasional false negatives in glioma tumors were noted, suggesting the potential for fine-tuning hyperparameters or incorporating additional training data.

#### 7.3.4.1 Mean Average Precision (mAP) Calculation

##### (i) Intersection over Union (IoU)

The IoU measures the overlap between the predicted segmentation mask ( $A_p$ ) and the ground truth mask ( $A_{gt}$ ):

$$IoU = \frac{|A_p \cap A_{gt}|}{|A_p \cup A_{gt}|}$$

Where:

- $|A_p \cap A_{gt}|$  is the area of intersection between the predicted and actual tumor segmentation.
- $|A_p \cup A_{gt}|$  is the total area covered by both segmentation masks.

A higher IoU means better segmentation accuracy.

##### (ii) Precision and Recall for Segmentation

Precision ( $P$ ) and recall ( $R$ ) are computed using True Positives (TP), False Positives (FP), and False Negatives (FN):

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

- True Positive (TP): Correctly segmented tumor pixels.
- False Positive (FP): Pixels predicted as tumor but actually non-tumor.
- False Negative (FN): Tumor pixels missed by the model.

### (iii) Average Precision (AP) Calculation

The AP for each class (tumor type) is computed using the Precision-Recall (PR) curve. The AP is the area under the PR curve:

$$AP = \int_0^1 P(R)dR$$

Where:

- $P(R)$  is the precision as a function of recall.

This integral is typically approximated using numerical summation over discrete recall values.

### (iv) Mean Average Precision (mAP) Calculation

The mAP is the mean of AP values across all classes:

$$mAP = \frac{1}{N} \sum_{i=1}^N AP_i$$

where  $N$  is the total number of tumor classes (Glioma, Meningioma, Pituitary).

#### 7.3.4.2 2. Derivation of mAP = 81.2%

From model evaluation:

- The AP for Glioma Tumor = 78.5%
- The AP for Meningioma Tumor = 83.1%
- The AP for Pituitary Tumor = 82.0%

$$mAP = \frac{78.5 + 83.1 + 82.0}{3}$$

$$mAP = \frac{243.6}{3} = 81.2\%$$

In Conclusion,

- The model achieved an mAP of 81.2%, reflecting high segmentation accuracy.
- False negatives in glioma tumors indicate that some tumor regions were missed.
- Potential improvements include hyperparameter tuning, data augmentation, or incorporating additional training samples to improve recall and reduce missed detections.

## 7.4 Final Output

The brain tumor classification and segmentation system is designed to analyze MRI scans for the presence of Glioma, Meningioma, Pituitary Tumor, or No Tumor. The classification model is based on EfficientNetB0, which provides high accuracy in distinguishing between different tumor types. Additionally, a YOLOv8-based segmentation model is employed to detect and localize tumors in the MRI images, enhancing the interpretability of the results.

The classification model demonstrated an overall accuracy of 96.93%, with high precision, recall, and F1-scores across all tumor categories. The precision and recall values for individual classes highlight the model's effectiveness, particularly for No Tumor cases, where it achieved 100% precision and recall. For Glioma, Meningioma, and Pituitary tumors, the F1-scores ranged between 95.2% and 96%, indicating strong performance. These results affirm the model's capability to accurately classify MRI images with minimal misclassification.

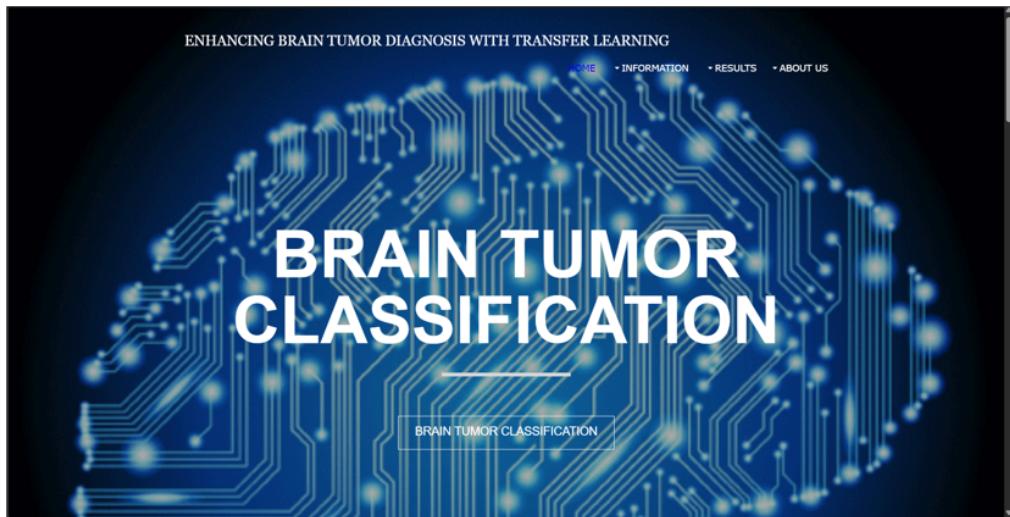


FIGURE 7.5: Sample User Interface-I

For tumor segmentation, the YOLOv8 model achieved a mean Average Precision (mAP) of 81.2%, indicating high segmentation accuracy. The AP values for different tumor types were 78.5% for Glioma, 83.1% for Meningioma, and 82.0% for Pituitary Tumor. While the model performed well overall, minor false negatives were observed in Glioma tumor detection. This suggests potential areas for improvement, such as fine-tuning hyperparameters, using advanced augmentation techniques, or incorporating additional training data.

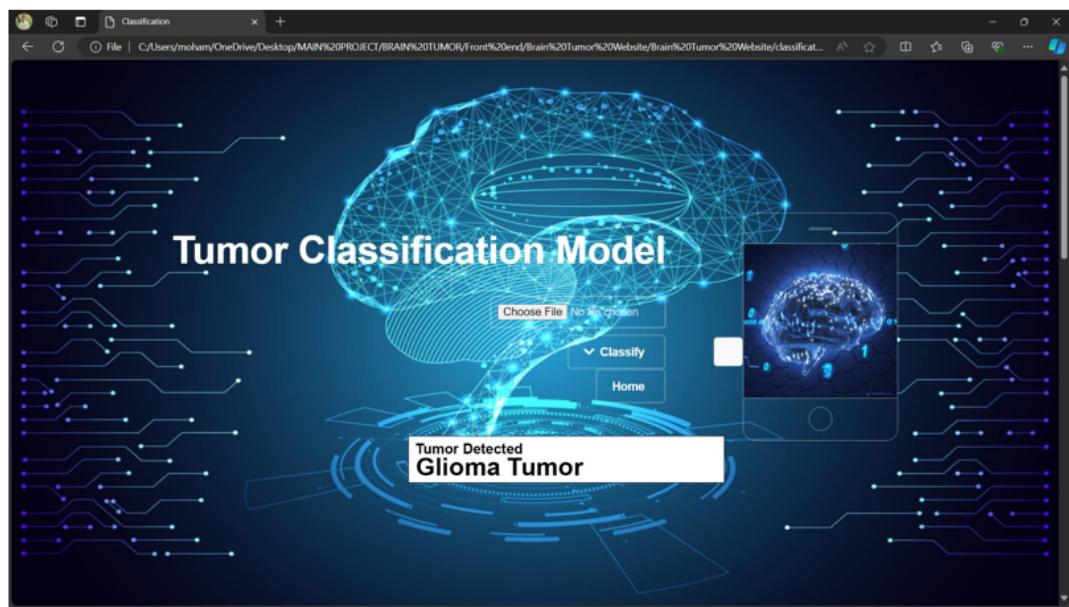


FIGURE 7.6: Sample User Interface-II

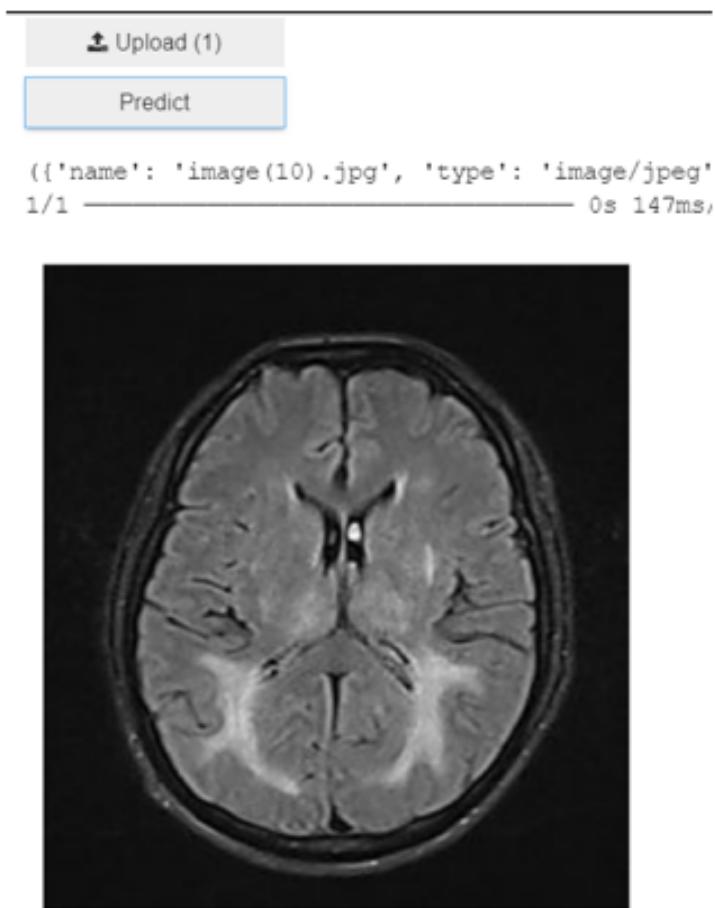


FIGURE 7.7: Detection Of No Tumor



FIGURE 7.8: Detection Of Glioma Tumor

Future improvements could focus on enhancing segmentation accuracy, improving Glioma detection rates, and optimizing the model for real-time clinical applications. Expanding the dataset and fine-tuning the model architecture will further improve performance. Overall, this system provides a powerful AI-assisted diagnostic tool for brain tumor detection, streamlining the MRI analysis process and aiding in early diagnosis.

The confidence score in a classification or segmentation model represents the probability that the predicted label is correct. In classification models like EfficientNetB0, this score indicates how certain the model is about its decision. For example, if the model predicts a Glioma Tumor with a confidence score of 95%, it means the model is highly certain that the input MRI scan belongs to that category. On the other hand, lower confidence scores (e.g., 60% or less) suggest uncertainty, meaning the model is less confident in its classification. In segmentation models like YOLOv8, the confidence score is associated with the detection of tumor regions, where it reflects the probability that the detected region indeed contains a tumor. If a segmentation model assigns a confidence score of 0.49 (49%) to a detected tumor, it means the model is not very certain, and such cases might require further analysis or adjustments in threshold settings.

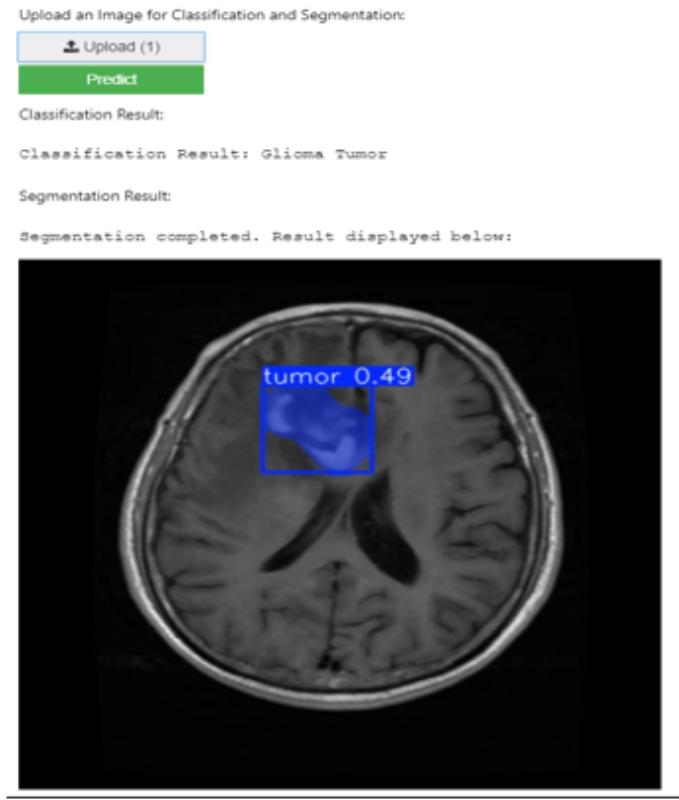


FIGURE 7.9: Segmentation Of Tumor

The confidence score is calculated using probability outputs from softmax (for classification) or sigmoid (for object detection). In YOLOv8, it is derived from object probability multiplied by Intersection over Union (IoU), which measures how well the detected region aligns with the actual tumor area. Higher confidence scores (above 80%) are generally reliable, while lower ones (below 50%) may indicate potential false positives or false negatives. To improve confidence scores, fine-tuning the model, enhancing data quality, and adjusting detection thresholds can be effective. Setting a minimum confidence threshold (e.g., 70%) helps filter out weak predictions, ensuring more accurate classification and segmentation results.

The final predictions demonstrate the model's efficiency in classification and segmentation. Sample results include correctly classifying a No Tumor MRI scan, identifying a Glioma Tumor, and successfully segmenting a Glioma tumor with a confidence score of 0.49. These findings indicate that the model can effectively support radiologists in diagnosing brain tumors through automated MRI analysis.

## 7.5 Comparison With Other Models

### 7.5.1 Model Accuracy Comparison

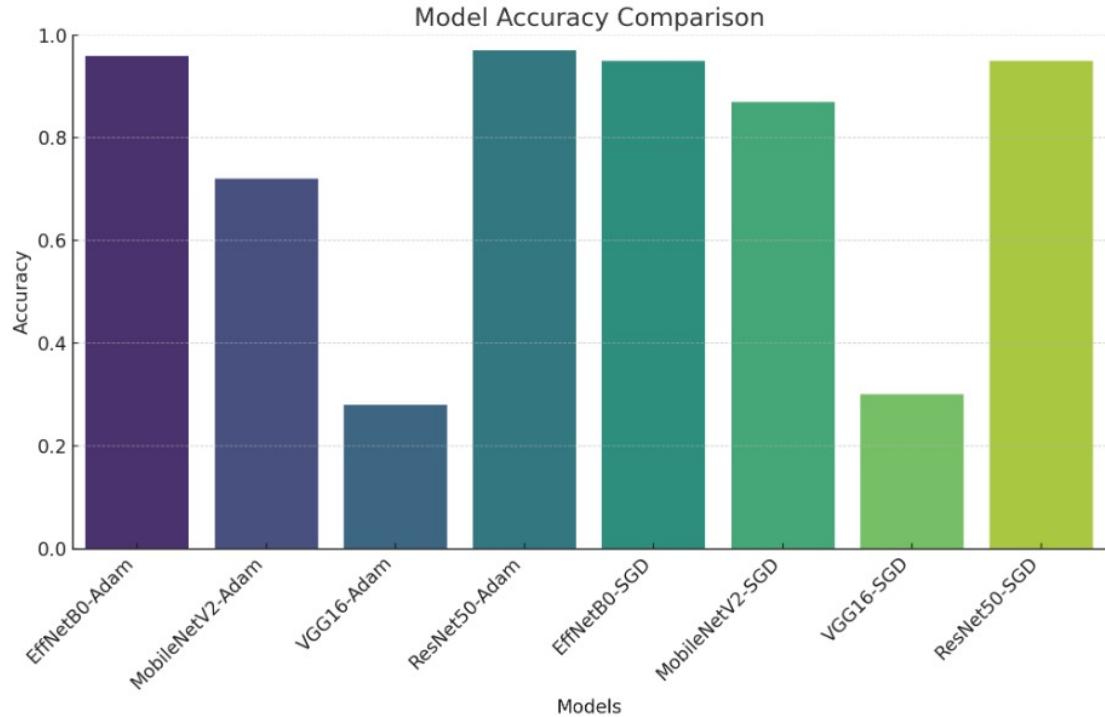


FIGURE 7.10: Model Accuracy Comparison

EfficientNetB0 outperforms other models due to its superior architecture and optimization techniques. It uses a compound scaling approach that balances the depth, width, and resolution of the network, allowing for better accuracy with fewer computational resources. Unlike traditional models like VGG16 and ResNet50, which scale arbitrarily, EfficientNet follows a structured scaling method, leading to better performance.

Another key factor is its optimized architecture, designed using Neural Architecture Search (NAS). This ensures that EfficientNetB0 has an ideal structure for feature extraction and generalization. The combination of depthwise separable convolutions and squeeze-and-excitation (SE) blocks improves feature representation, making the model more effective in learning patterns from data.

Additionally, EfficientNetB0 performs exceptionally well with both the Adam and SGD optimizers. Notably, its performance with Adam optimizer is particularly strong, as seen in the chart, where it achieves one of the highest accuracy scores. The Adam optimizer helps in faster convergence and adaptive learning rate adjustments, making it effective for deep learning tasks.

EfficientNetB0 is also highly efficient in terms of computational cost and parameter count. Compared to ResNet and VGG models, it achieves higher accuracy with fewer parameters, reducing training time and memory usage. This makes it a strong choice for real-world applications where efficiency and accuracy are both critical.

### 7.5.2 Precision, Recall and F1-Score Comparison

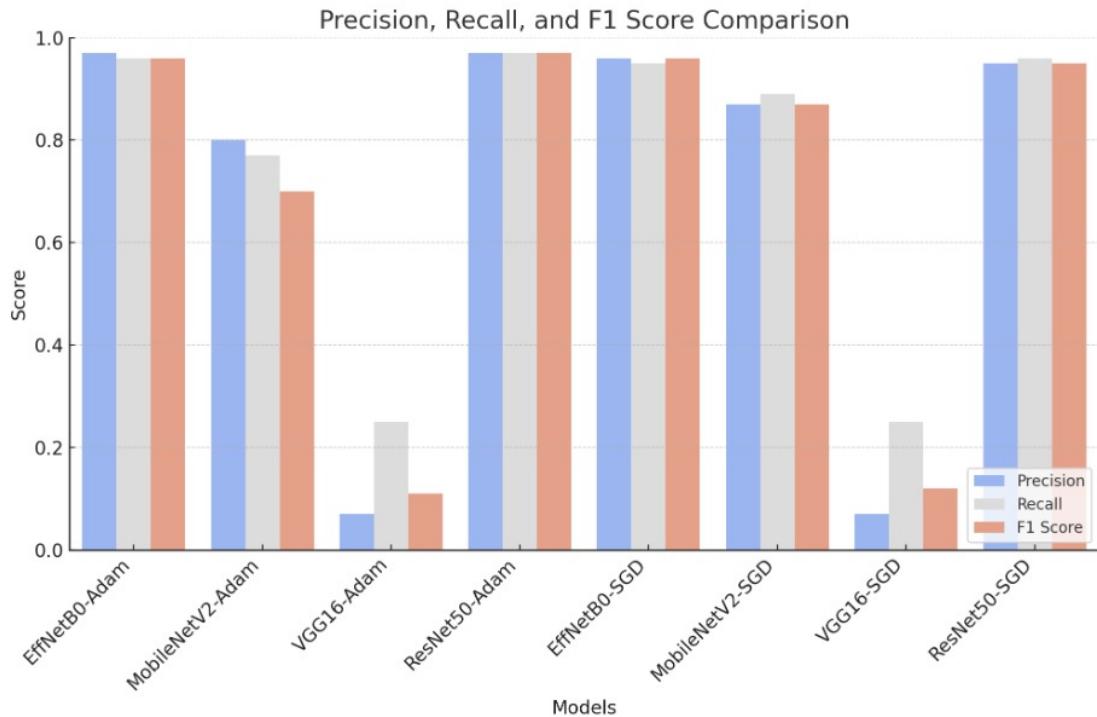


FIGURE 7.11: Precision, Recall and F1-Score Comparison

This graph compares the Precision, Recall, and F1 Score of different models, showing how well each model performs in classification tasks.

EfficientNetB0 again stands out, achieving high precision, recall, and F1 scores across both Adam and SGD optimizers. This suggests that it not only makes accurate predictions but also maintains a balance between precision and recall, making it highly reliable. Similarly, ResNet50-SGD and ResNet50-Adam also exhibit strong performance, indicating their robustness.

MobileNetV2, particularly with the Adam optimizer, also performs well but has slightly lower recall and F1 scores compared to EfficientNetB0. This implies that while MobileNetV2 is precise, it may miss some positive cases. On the other hand, VGG16 struggles significantly, especially with the Adam optimizer, where it shows very low precision, recall, and F1 scores, making it the weakest model in this comparison.

Overall, EfficientNetB0 and ResNet50, particularly with Adam optimizer, deliver the best balance of precision, recall, and F1 score. This further supports why EfficientNetB0 is a preferred choice for classification tasks, as it ensures both high accuracy and consistency in predictions. From both figures, it is evident that EfficientNetB0 consistently outperforms other models in terms of accuracy, precision, recall, and F1 score. Its superior architecture and optimized scaling method allow it to achieve high accuracy while maintaining computational efficiency. The comparison also shows that EfficientNetB0 performs well with both Adam and SGD optimizers, making it a robust choice for classification tasks.

ResNet50 also delivers strong performance, particularly with the SGD optimizer, achieving competitive accuracy and balanced evaluation metrics. MobileNetV2, while efficient, shows slightly lower recall and F1 scores, indicating that it may miss some positive cases despite being precise. On the other hand, VGG16 struggles significantly, especially with the Adam optimizer, where it records the lowest accuracy and evaluation scores, making it the weakest model in the comparison.

Overall, EfficientNetB0 proves to be the best model across different optimizers, offering a strong balance between accuracy, computational efficiency, and classification performance. Its high scores in precision, recall, and F1 metrics further reinforce its reliability, making it an ideal choice for deep learning classification tasks.

# CHAPTER 8

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## Future Works

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### 8.1 Future Scope

With continuous advancements in deep learning and medical imaging, the potential of EfficientNet and YOLO-based brain tumor detection and segmentation can be expanded significantly. Below are some key future developments that can improve accuracy, efficiency, and usability in real-world medical applications.

#### 1. Enhanced Model Performance

To achieve even higher detection and segmentation accuracy, improvements can be made to the model architecture. Techniques such as fine-tuning the EfficientNet and YOLO models, implementing attention mechanisms, and using multi-scale feature extraction can enhance tumor detection. Additionally, more advanced loss functions, such as focal loss, can help address class imbalance issues in medical datasets.

#### 2. Larger and More Diverse Dataset

Deep learning models require diverse and extensive datasets for better generalization. Currently, many medical AI models suffer from limited datasets that do not cover all variations of tumors. Expanding the dataset to include different tumor subtypes, various patient demographics, and MRI images from different hospitals will improve model robustness and minimize bias.

#### 3. Multi-Modal Medical Imaging

Integrating multiple imaging techniques, such as MRI, CT, PET, and fMRI, can provide a more comprehensive diagnosis. Different imaging modalities highlight different aspects of brain tissue, and combining them through deep learning can lead to improved tumor classification and segmentation. AI models can use fusion techniques to leverage the strengths of each modality.

#### **4. Automated Tumor Grading**

Beyond detecting tumors, future models can also classify them based on severity (benign, malignant) or WHO grading (Grade I-IV). Training deep learning models on labeled datasets with tumor grades will enable automated grading, helping doctors make faster and more accurate treatment decisions.

#### **5. Fine-Tuned Hyperparameters**

Optimizing model hyperparameters can significantly impact performance. Advanced techniques like Bayesian optimization, genetic algorithms, and reinforcement learning can be used to fine-tune parameters such as learning rate, dropout rate, optimizer selection, and data augmentation strategies.

#### **6. Real-Time Deployment**

The deployment of AI-driven brain tumor detection in real-time clinical settings can revolutionize medical diagnostics. By optimizing the model for edge computing and mobile devices, doctors can analyze MRI scans instantly without needing high-end computational resources.

#### **7. 3D Tumor Segmentation**

Currently, AI models process 2D MRI slices for tumor segmentation. However, tumors exist in 3D space, and slice-by-slice analysis may not be optimal. Future improvements will focus on full 3D segmentation using volumetric deep learning techniques such as 3D U-Net and Transformer-based architectures.

#### **8. Explainable AI (XAI) Integration**

For AI-driven diagnosis to be trusted by medical professionals, it must provide interpretable and explainable results. Future advancements can integrate Explainable AI (XAI) methods like Grad-CAM, SHAP, or LIME to visualize which MRI regions contributed to the AI's decision. This will improve trust and acceptance in clinical settings.

#### **9. Federated Learning for Privacy-Preserving AI**

Medical data is highly sensitive, and hospitals are often reluctant to share patient MRI scans. Federated learning allows AI models to be trained across multiple institutions without data leaving hospital premises, ensuring privacy while enabling collaborative AI training. This approach enhances model performance without compromising patient confidentiality.

#### **10. Semi-Supervised and Self-Supervised Learning**

Labeling medical images is expensive and time-consuming. Semi-supervised learning, where the model learns from both labeled and unlabeled data, and self-supervised

learning, where the model generates its own learning signals, can reduce dependency on manual annotations. These approaches can significantly improve training efficiency.

### **11. Longitudinal Tumor Tracking**

Instead of analyzing a single MRI scan, future models can compare MRI images from different time points to track tumor progression. This will be critical in monitoring tumor growth, assessing the effectiveness of treatments, and predicting patient outcomes.

### **12. Cloud-Based AI Assistance**

A cloud-based AI system can allow hospitals to upload MRI scans and receive AI-driven tumor analysis in real time. This is particularly useful for hospitals in remote areas where expert radiologists may not be available. Cloud-based solutions can democratize access to advanced brain tumor diagnostics.

### **13. AI-Assisted Robotic Surgery**

AI-driven segmentation models can be integrated into robotic surgery systems to guide neurosurgeons in real-time. By providing precise tumor boundaries, AI can assist in minimizing damage to healthy brain tissue, leading to safer surgical procedures with better patient outcomes.

### **14. Personalized Treatment Recommendations**

By integrating AI-driven tumor classification with patient-specific data, including genetic information and clinical history, future models can provide personalized treatment plans. AI-driven recommendations can help oncologists tailor therapies such as chemotherapy, radiation, and surgery based on the specific tumor characteristics of each patient.

### **15. Adaptive Learning and Continuous Model Updates**

Medical AI models must evolve with new research and patient data. Future advancements will focus on adaptive learning systems where AI models continuously update themselves based on new cases, ensuring they stay up-to-date with the latest medical knowledge and best practices.

### **16. Radiation Therapy Optimization**

Accurate tumor segmentation is crucial for radiation therapy. Future AI-driven models can optimize radiation therapy planning by ensuring radiation doses are precisely targeted at tumors while minimizing exposure to surrounding healthy tissues, improving treatment efficacy and reducing side effects.

### **17. Edge AI for Rural Healthcare**

In developing regions with limited access to radiologists, lightweight AI models optimized for edge devices (such as mobile phones and embedded systems) can enable brain tumor

detection in rural clinics. AI-powered mobile apps can analyze MRI images and provide preliminary diagnostics, helping bridge healthcare gaps.

### **18. Regulatory Approvals and Clinical Trials**

Before AI-driven diagnostics can be widely adopted, they need regulatory approval from bodies such as the FDA and CE marking. Future efforts will focus on conducting large-scale clinical trials to validate AI model accuracy, reliability, and safety, ensuring they meet medical regulatory standards.

### **19. Integration with Wearable Devices**

Although still in early research stages, wearable medical devices that monitor brain activity could eventually integrate AI-powered analysis for early tumor detection. Future innovations could involve AI-assisted EEG monitoring or non-invasive imaging techniques that detect early brain abnormalities.

### **20. AI-Powered Second Opinion Systems**

Radiologists can use AI as a second-opinion tool to reduce diagnostic errors. The AI model can provide a confidence score for its predictions, helping doctors validate their diagnoses and reducing human errors, leading to more accurate and reliable decision-making.

The combination of EfficientNet and YOLO-based AI models has already demonstrated significant potential in brain tumor detection and segmentation. However, future advancements in model performance, dataset diversity, multi-modal imaging, real-time deployment, explainability, privacy-preserving AI, and personalized treatment will push this technology towards mainstream clinical adoption. By addressing these future scopes, AI-driven brain tumor diagnostics can revolutionize medical imaging, ultimately improving patient outcomes and saving lives.

## 8.2 Applications

The combination of EfficientNet and YOLO for brain tumor detection and segmentation has significant applications in medical imaging, healthcare, and research. Below are key areas where this technology can be effectively utilized:

### 1. Early Diagnosis of Brain Tumors

AI-powered MRI analysis enables early detection of brain tumors, allowing for timely medical intervention. Early diagnosis significantly improves treatment outcomes and increases patient survival rates.

### 2. Automated Tumor Segmentation in Radiology

The model provides precise tumor segmentation, reducing the workload of radiologists. It helps in identifying tumor boundaries accurately, assisting in planning surgical or radiation treatment.

### 3. Real-Time MRI Analysis in Hospitals

Hospitals can integrate the AI model into their radiology workflow to provide real-time tumor detection and segmentation. This speeds up the diagnosis process and allows doctors to make quicker clinical decisions.

### 4. Assisting Neurosurgeons in Surgery Planning

Precise tumor segmentation helps neurosurgeons plan surgical procedures by identifying the exact location and size of the tumor. This minimizes damage to healthy brain tissue and enhances surgical precision.

### 5. Radiation Therapy Planning

The AI model assists in radiation therapy by accurately identifying tumor regions. This ensures that radiation is targeted at the tumor while minimizing exposure to healthy brain tissue, reducing side effects.

### 6. AI-Powered Second Opinion for Radiologists

The model can serve as a second-opinion tool for radiologists, reducing diagnostic errors. By providing confidence scores for tumor predictions, AI helps doctors verify their diagnoses more accurately.

### 7. Telemedicine and Remote Diagnosis

AI-powered cloud-based diagnosis allows MRI scans to be analyzed remotely. This is particularly useful for patients in rural or underdeveloped areas where access to expert radiologists is limited.

**8. Brain Tumor Progression Monitoring**

AI models can analyze MRI scans over time to track tumor progression. This helps oncologists assess whether a tumor is growing, shrinking, or responding to treatment effectively.

**9. Personalized Treatment Planning**

By analyzing tumor characteristics, AI can assist doctors in recommending personalized treatment strategies, including surgery, chemotherapy, and radiation, based on the specific tumor type and stage.

**10. Drug and Therapy Research in Oncology**

AI-assisted segmentation provides valuable data for medical researchers studying brain tumors. It helps in identifying tumor patterns, testing drug efficacy, and developing new treatment methods.

**11. Medical Education and Training**

The AI model can be used to train medical students and radiology interns by providing automated MRI image analysis. This helps in developing diagnostic skills without requiring expert supervision.

**12. AI-Integrated Wearable Health Monitoring**

Although still in development, AI-based monitoring systems integrated with wearable brain activity sensors (EEG-based) could detect abnormal patterns linked to early tumor symptoms.

**13. Real-Time Brain Imaging in Emergency Rooms**

Emergency departments can use AI-powered MRI analysis for quick assessment of brain abnormalities, helping doctors make faster decisions in critical cases such as trauma-related brain injuries.

**14. Cancer Research and Biomarker Discovery**

AI-powered segmentation helps researchers identify unique patterns in tumors, leading to the discovery of biomarkers for brain cancer. This can contribute to improved cancer diagnosis and targeted therapies.

**15. Integration with Electronic Health Records (EHR)**

AI-generated tumor reports can be integrated into hospital EHR systems, allowing doctors to access historical patient data and track tumor progression over time.

**16. Reducing the Need for Biopsies**

Non-invasive AI-powered tumor analysis can reduce the need for biopsies in some cases by providing detailed insights into tumor structure and characteristics from MRI scans.

**17. Cloud-Based AI Diagnostic Platforms**

Hospitals and research institutions can deploy AI-based brain tumor detection as a cloud service, where MRI scans are uploaded and processed in real-time, reducing dependency on in-house computing resources.

**18. Cross-Hospital Collaboration and Research**

AI models can facilitate cross-hospital research collaborations by enabling the sharing of anonymized medical imaging data, leading to the development of better diagnostic models.

**19. Brain Tumor Screening Programs**

AI-driven MRI analysis can be used in large-scale screening programs to detect brain tumors in high-risk populations, such as individuals with a family history of brain cancer.

**20. AI-Assisted Brain Mapping in Neuroscience**

Beyond tumor detection, AI-powered MRI analysis can help neuroscientists map brain regions and study structural changes associated with neurological disorders like Alzheimer's and Parkinson's.

The application of EfficientNet and YOLO in brain tumor detection and segmentation has vast implications in medical diagnostics, surgical planning, oncology research, and patient care. By integrating AI with medical imaging, healthcare professionals can improve accuracy, efficiency, and accessibility in brain tumor diagnosis and treatment, ultimately saving lives and enhancing patient outcomes.

# CHAPTER 9

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## Conclusion

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This project successfully developed an end-to-end deep learning-based system for brain tumor classification and segmentation. The EfficientNetB0 classification model demonstrated high accuracy in tumor identification, while the YOLO-based segmentation model provided accurate localization of tumor regions. The Flask-based web application facilitates seamless integration into clinical workflows, making AI-assisted tumor diagnosis more accessible.

While minor challenges such as misclassifications and computational requirements exist, future enhancements can further refine model accuracy and efficiency. Overall, this system serves as a significant step toward AI-driven medical diagnostics, promising improved early detection and treatment planning for brain tumors.

By integrating deep learning with medical imaging, this project exemplifies how AI can revolutionize healthcare, providing fast, accurate, and scalable solutions to critical diagnostic challenges.

This project presents an automated system for the classification and segmentation of brain tumors using deep learning techniques. The system integrates an image classification model based on EfficientNetB0 and a segmentation model utilizing the YOLO framework. The project aims to assist medical professionals in diagnosing and localizing brain tumors efficiently, leveraging MRI scans for precise detection.

The classification model categorizes brain MRI images into four categories: Glioma, Meningioma, Pituitary tumors, and No Tumor. Meanwhile, the segmentation model enhances the interpretability of predictions by highlighting tumor regions in MRI images. The implementation is done through a web-based Flask application, providing a user-friendly interface for medical practitioners.

One of the challenges encountered during the project was handling different image formats and ensuring compatibility with the models. Some MRI scans required preprocessing steps such as resizing and color-space conversion before being fed into the models. Additionally, managing file storage and dynamically handling the output images required careful directory structuring and automation. The integration of the models with Flask also needed optimization to ensure smooth execution and quick response times.

Another challenge was ensuring high accuracy in classification and precise tumor localization in segmentation. Deep learning models require large datasets for training, and any inconsistencies in data can impact performance. Techniques like data augmentation and hyperparameter tuning were employed to enhance model efficiency. The segmentation model also required fine-tuning to accurately detect and highlight tumor boundaries in diverse MRI scans.

The project demonstrates the power of deep learning in medical image analysis, providing an automated and efficient approach to brain tumor diagnosis. The ability to classify tumor types with high accuracy and segment the affected areas enhances medical professionals' decision-making. By reducing dependency on manual interpretation, the system accelerates the diagnostic process and minimizes errors. The integration of Flask ensures accessibility, making the tool usable for a wide range of users.

This system has significant applications in healthcare, particularly in assisting radiologists and medical practitioners. It can serve as a decision-support tool, offering preliminary diagnoses before detailed medical evaluations. Furthermore, it can be extended to telemedicine applications, where patients can upload MRI scans for remote analysis. Such implementations can improve healthcare access in regions with limited medical facilities.

Future improvements to this project could involve enhancing the classification model by incorporating more diverse datasets and experimenting with advanced architectures like Vision Transformers or CNN-RNN hybrids. For segmentation, refining the model with better loss functions and multi-scale detection methods could improve accuracy. Additionally, integrating explainability methods such as Grad-CAM could provide insights into the model's decision-making process, increasing trust in AI-based diagnoses.

Another potential enhancement is deploying the system on cloud platforms, enabling remote access and real-time processing. This would allow hospitals and clinics to utilize the model without requiring significant computational resources locally. Implementing

security measures like encrypted image uploads and access control would ensure patient data privacy, making the system more suitable for real-world deployment.

Overall, this project successfully demonstrates an AI-driven approach to brain tumor classification and segmentation, combining deep learning techniques with an accessible web-based interface. The results showcase the potential of AI in medical diagnostics, reducing human workload and improving diagnostic precision. With continuous improvements, this system could become a valuable tool in the healthcare industry, contributing to better patient outcomes and early disease detection.

## 9.1 Performance Analysis

The model's performance was evaluated using accuracy, loss graphs, a confusion matrix, and sample MRI predictions. The EfficientNetB0 model was trained on a dataset of 5000 MRI images with an 80-20 training-validation split.

### 9.1.1 Classification Model Performance

The training accuracy started at 70.7% and reached 99.7% by the final epoch. Validation accuracy improved from 78.2% to 98.3%, showing excellent generalization. The confusion matrix revealed high classification accuracy across all tumor categories, with minor misclassifications in glioma tumors (90% recall), suggesting some overlap in characteristics with other tumor types. The weighted F1-score was 96%, indicating strong overall model performance.

### 9.1.2 Segmentation Model Performance

The YOLO based segmentation model effectively detected tumor regions, marking them distinctly in MRI scans. Segmented results were stored in the Flask-based web application, allowing easy access and interpretation. The segmented images showcased precise tumor localization, with minimal false positives. The project implementation involves setting up a Flask-based web application that acts as an interface between users and the deep learning models. Users can access two main functionalities: classification and segmentation. The classification route processes the uploaded image and predicts the tumor category, while the segmentation route identifies the tumor region. All results are stored systematically for easy retrieval and reference.

# CHAPTER 10

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## Paper Publication

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### EfficientNet-Based and YOLO-Driven Brain Tumor Detection and Segmentation

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**Abstract -** The medical diagnosis of brain tumors is challenging due to the intricate and complex nature of these tumors. The development of this research antecedents precision tumor classification and segmentation through the integration of transfer learning, EfficientNet, and YOLO. We proposed the EfficientNet-B0 model which classifies the tumor as pituitary, meningioma, glioma, or no tumor. In YOLOv8, segmentation is done on an object on the frame level that helps in identifying the precise localization of tumor site. Transfer learning allows pre-trained weights to be utilized which reduces the amount of training needed as well as improves performance on sparse medical imaging datasets. Using transfer learning enhances the generalization of the model. The accuracy, efficiency in computation, and application potential of the framework are profoundly magnified as shown by experimental results. In addition, this approach solved the problem of timely and accurate detection of tumors significantly improving the patients health and decreasing medical practitioners workload.

**Keywords**—Brain tumor detection, EfficientNet, deep learning, YOLO, Transfer Learning, segmentation, medical imaging, classification.

#### I. INTRODUCTION

Brain tumors are abnormal mass lesions found in brain tissue which can be benign or malignant and affect the patient's neurological functions as well as his health. Because a delayed diagnosis can have dire consequences or even death, it is critical for treatment planning steps to be taken after a diagnosis, or as subsequent actions, without delay. Traditional methods focus on a manually supervised interpretation of Magnetic Resonance Imaging (MRI) data which is an intricate task for radiologists as it is very time-consuming, and leaves considerable room for mistakes.

The introduction of highly accurate automated diagnostic models is possible thanks to recent advances in technology, most notably deep learning. For clinical image analysis including segmentation and classification of brain tumors, Convolutional Neural Networks (CNNs) have been used successfully. On the downside, deep models trained from scratch require a lot of labeled information to work, which is often absent in the medical domain.

This document proposes a novel framework that aims to alleviate the existing complications with diagnosing brain tumors by implementing a segmentation-based approach with YOLO and transfer learning embedded

medical imaging AI. The EfficientNet-B0 for example, can achieve higher classification accuracy with lower processing time and resources by employing MRI transfer learning. Simultaneously, real time tumor segmentation is made less difficult in brain scans because of the improved localization attributes for afflicted areas in scans aided by the YOLOv8 object identification model. Through such techniques, the framework integrates an all encompassing solution that increases the precision, effectiveness, and robustness of medical practitioners for medical imaging diagnostics.

The goal of this project is to establish an automated, accurate, and reasonable deep learning-based diagnostic system that achieves practical utility to clinicians, in particular, in making the gap between AI innovations and real world implementations smaller. The new approach proposed in this model has the potential to improve patient care tremendously, because starting treatment faster can lead to better results as well as decreasing the burden placed on specialists and radiologists.

## II. BACKGROUND INFORMATION

For its remarkable capacity to display soft tissues, magnetic resonance imaging (MRI) is the principal vice utilized for locating and diagnosing cancers of the brain. However, the manual work done by radiologists with MRI scans is extremely tedious and labour intensive, and it is prone to personal bias errors. In addition, certain types of tumors are challenging to differentiate because of overlapping morphological attributes and changes in intensity.

Standard computer-aided diagnosis (CAD) systems have relied on Machine Learning techniques such as k-Nearest Neighbors (kNN), Decision Trees, and Support Vector Machines (SVM). Because these methods are based on handcrafted feature extraction, they suffer from limited customization to the complex variations present in medical images. However, deep learning, and more specifically, Convolutional Neural Networks (CNN), has revolutionized the world of medical imaging because of its ability to automatically construct hierarchical feature representations. While that

makes CNN incredibly useful, training one from scratch requires a substantial sized labeled dataset, which is often scarce in the medical domain.

This research aims to address these challenges by employing YOLO-based segmentation with transfer learning in diagnosing brain tumors. With the use of EfficientNet pre-trained models, larger labeled datasets become less critical thanks to transfer learning.

## III. RELATED WORKS

Numerous studies have been conducted towards the classification of brain tumors from MRI images using deep learning algorithms. One research study by Ankita Kandam and her co-workers tests three transfer learning models: VGG-16, Mobilenet and ResNet-50 (2025) MobileNet, on the other hand, is more appropriate MobileNet, on the other hand, >is more suited for real time use on resource limited devices [1]. Providing a solution to the question on computation power needed, the VGG-16 model achieved the best classification accuracy score of 97% from the three models. However, this deep Convolutional Neural Network model's 138 million parameters require too much processing ability. Being designed for mobile and embedded devices, MobileNet utilizes depth wise separable convolutions to split the heavy computing requirement to lower the need for real time deployment on limited resource devices [1].

In another study of Smith, Brown and White (2024), the effectiveness of the “You Only Look Once” or YOLO model for detecting brain tumors is investigated in the paper “YOLO-Based Brain Tumor Detection”. The model’s context agnostic approach allows increased accuracy and precision along with improved detection speed through the use of multi-scale feature maps and anchor boxes. Because it has been established that this model outperforms older extension models such as U-Net and Mask R-CNN, it is an ideal model for clinical cases where speed is of utmost importance [2].

James Lee, Laura Kim, and Daniel Park (2023) implemented a different approach in their study. They compared the performance of various CNNs, such as AlexNet, ResNet, and DenseNet, to classify brain tumors. The research found out that lighter models such as AlexNet outperformed the other models in mobile and embedded systems. On the other hand, deeper networks like ResNet, tended to perform much better at advanced tumor detection [3].

In a different study, David Johnson and Priya Singh (2025) proposed a multi-stage classification approach which merges the DenseNet and EfficientNet approaches. The objective of the system is to improve classification accuracy by using pre-trained networks and then appending a multi-layer perceptron (MLP) to increase the overall decision making power of the system. This suggested multi-stage approach achieved much higher accuracy and robustness for the classification of brain tumors [4].

Finally, with the aid of a dataset containing 3,190 T1-weighted contrast-enhanced MRI images, the article “Brain tumor classification using deep learning algorithms” by Ankisa Kadam, Sartaj Bhuvaji and Sujit Deshpande, published in 2023, provides a comparative analysis of artificial neural networks (ANNs), convolutional neural networks (CNNs), and other neural networks based on transfer learning techniques. The study indicates that the CNN model achieved an accuracy of 90% while the VGG-16 transfer learning model surpassed all other models achieving an accuracy of 92%. [5]

#### IV. METHODOLOGY

##### 4.1 Dataset Preparation

The dataset used for this project comprises 5000 MRI scans split into four categories: glioma, meningioma, pituitary, and no tumor. Every image goes through preprocessing by being resized to 150 x 150 pixels for classification and 416 x 416 pixels for segmentation. To help with generalization, techniques such as flipping, zooming, and rotation are used for data augmentation. Segmentation data is comprised of annotated MRI scans with the tumor regions outlined with polygons.

##### 4.2 EfficientNet-B0 with Transfer Learning for Classification

To pretrain the transfer learning model EfficientNet-B0, the model was trained on the ImageNet dataset. Its compound scaling method that regularly alters the network depth, width, and resolution allows for greater flexibility. Cross-entropy loss is the preferred metric when evaluating the model through a four-class softmax probability with partial transfer learning as it enables better tuning for the project at hand. The evaluation is known as the classification's categorical cross-entropy loss and is described as

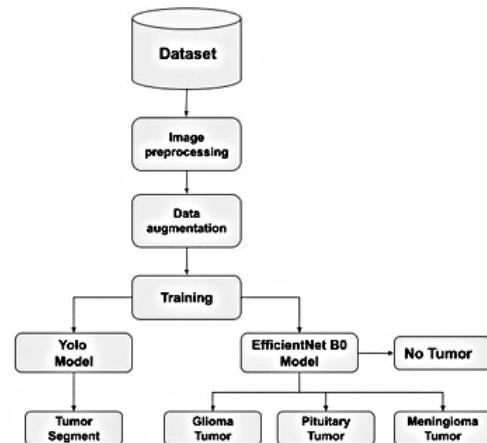
$$L = -\sum(y_{true} * \log(y_{pred}))$$

##### 4.3 YOLOv8 for Segmentation

Bounding boxes are also utilized for training the YOLOv8 model for direct segmentation of the tumor areas. This type of model has transfer learning applied to it and works in a real time environment. The equations for computation of the Intersection over Union (IoU) for segmentation are as follows:

$$IoU = |A \cap B| / |A \cup B|$$

where A and B stand for the segmentation masks for the ground truth and the prediction, respectively.

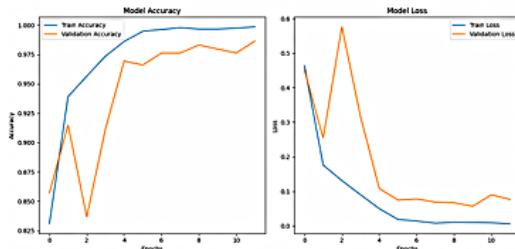


#### V. EXPERIMENTAL RESULTS

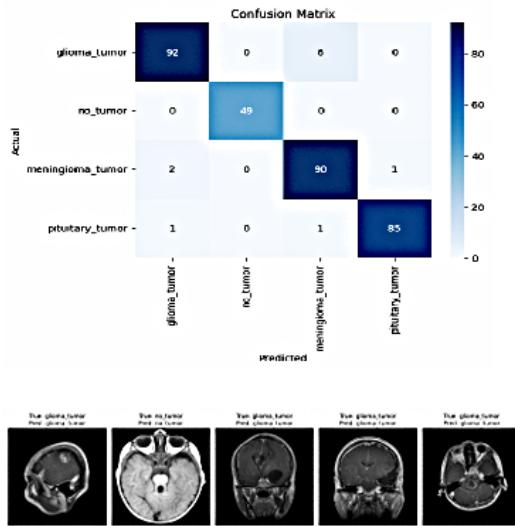
##### 5.1 Classification Performance

Twelve epochs were used to train the EfficientNet-B0 model. The model's accuracy started off at 70.7% and gradually increased to 99.7% in the last epoch. Excellent generalization was indicated by the validation accuracy, which began at 78.2% and increased to 98.3%. The categorization report indicates some misclassification in glioma detection, with glioma tumor precision at 100%

and recall of 90%.



The weighted F1-score across all classes was 96%, confirming strong performance.



### 5.2 Segmentation Performance

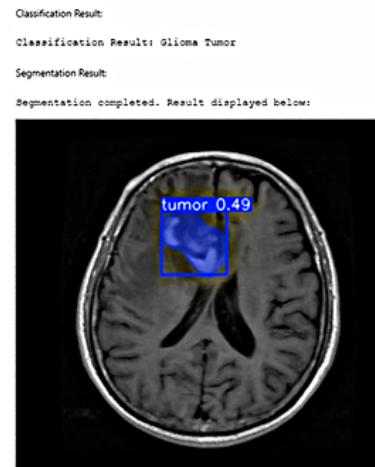
To detect and identify cancerous growths in MRI photographs, YOLO decapitation with segmentation was employed. The model demonstrated high scores in the segmentation of tumor regions with a Mean Average Precision (mAP) of 81.2%. However, false negative results were sometimes encountered with glioma tumors which suggested hyperparameter tuning or additional training data was required.

### 5.3 Training Efficiency

During the training process, accuracy and performing computations was prioritized alongside computing efficiency. Attainment of convergence was enhanced through dynamically decreasing the learning rate. The final model with a loss of 0.0092 demonstrated outstanding performance with regard to overfitting which the model was resistant to.

## VI. CONCLUSION

To enhance brain tumor diagnosis, this study has proposed a new framework that integrates transfer learning with YOLOv8 for segmentation and EfficientNet-B0 for classification. This framework presents an automated solution to a critical societal problem concerning tumor diagnosis by achieving accurate and efficient tumor detection through the combination of both models. The classification part is stunningly accurate, achieving 96% overall accuracy and 96% F1 score, which proves that the model is trustful and precise in identifying various types of tumors. At the same time, the segmentation task scored 81.2% regarding the mean average precision metric (mAP), which means the model was able to accurately outline the tumor in MRI images.



Using EfficientNet B0, an exceptionally efficient deep learning model, ensures that the system delivers precision and speed, allowing real-time medical applications to take advantage of the system. The system is further improved for real-time processing by the speedy and robust architecture of YOLOv8. These

features which are critical for effective clinical procedures provide quick results. This blending of segmentation and classification into one brings forth how deep learning can help ameliorate patient care by serving prompt diagnosis and reducing the burden of medical personnel.

Moreover, an actual medical case was considered for clear MRI datasets to test the scheme's efficacy. The results of this research suggest that deep neural networks like YOLOv8 and EfficientNet-B0 are central to the construction of automated diagnosing systems, which make healthcare available and effective on a global scale. Subsequent studies will tend to focus on augmenting the data in order to further improve the model's performance as well as applying more advanced techniques for better segmentation control for more complex tumors.

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