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ABSTRACT

This project presents a deep learning-based system for the detection and classification of brain tumors from MRI images, addressing the critical need for accurate and efficient diagnostic tools in healthcare. Using a convolutional neural network (CNN) architecture enhanced with transfer learning, the system was trained to identify and classify gliomas, meningiomas, pituitary tumors, and non-tumor cases. The model achieved high accuracy, precision, recall, and F1 scores across all classes, demonstrating its reliability in tumor detection. Advanced image preprocessing techniques and data augmentation were employed to improve model generalization and mitigate overfitting. The system also features a user-friendly web-based interface for clinicians to upload MRI scans, review results, and generate automated diagnostic reports. Despite challenges such as limited datasets, computational resource requirements, and initial integration issues, the project successfully developed a robust solution for brain tumor detection. Future enhancements will focus on expanding the dataset, improving real-time processing capabilities, and integrating explainable AI techniques to foster greater trust among clinicians. This system has the potential to significantly enhance diagnostic accuracy and efficiency in clinical settings.

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CHAPTER 1

INTRODUCTION

1.1 Overview

Brain tumors arise from uncontrolled cell division, leading to abnormal cell masses that can interfere with normal brain operations and harm healthy tissues. These tumors are categorized as either benign (low-grade), which grow slowly and do not spread, or malignant (high-grade), which are aggressive, grow quickly, and have the potential to metastasize. Brain MRI serves as a crucial imaging method for detecting tumors, thanks to its high resolution and capability to offer detailed insights into brain structures. There has been an increase in automated techniques for tumor identification and classification using MRI, with Support Vector Machines (SVM) and Neural Networks (NN) historically being used. More recently, deep learning models have surfaced as a more effective option, capable of understanding intricate data relationships with fewer nodes than traditional architectures like SVM or K-nearest neighbors (KNN). As a result, deep learning has emerged as a predominant technique in the field of medical image analysis and other health informatics areas, markedly enhancing the possibilities for detecting and diagnosing brain tumors.

1.2 Background and Motivation

The brain acts as the body's central control system, and various brain disorders have been recognized in recent years. Diagnostic tools for brain diseases are becoming more intricate and represent a significant focus for ongoing research; however, the implementation of AI in diagnosing brain disorders has improved the accuracy and reliability of disease detection and prediction. Automated techniques for non-invasively analyzing brain images have become crucial, given that brain diseases can be life-threatening and are a major contributor to mortality rates in developed countries. The incorporation of AI in brain tumor surgeries can result in safer and more effective treatment outcomes. A key challenge persists in the disparity of knowledge between healthcare professionals and experts in data science. This project stems from the necessity for a tool that can assist radiologists in detecting brain tumors with greater precision and efficiency, ultimately leading to enhanced patient outcomes.

1.3 Statement of the Problem

The problem statement of this study outlines several pivotal issues concerning the detection of brain tumors via MRI scans. Firstly, the precision of detecting brain tumors is hindered by the dependence on doctors to

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manually locate tumors, which not only impacts accuracy but also makes the process time-consuming. Secondly, the task of segmenting tumors poses considerable difficulties due to the intricate nature of brain anatomy, complicating the accurate delineation of tumor edges. Ultimately, the main obstacle is the identification of brain tumors amidst variations in tumor location, shape, size, and intensity across different individuals, alongside the frequently unclear and irregular borders of the tumors. These elements together emphasize the necessity for sophisticated automated solutions to improve diagnostic precision and efficiency in clinical settings.

1.4 Aim and Objectives

Aims

The objective of this project is to create an automated system for the precise identification and classification of brain tumors through MRI images.

Objectives

1. To develop a deep learning model that can categorize brain tumors as glioma, meningioma, pituitary, or indicate the absence of a tumor.
2. To assess the model's effectiveness through metrics like accuracy, precision, recall, F1-score, and the confusion matrix.
3. To create a user-friendly web interface that allows clinicians to upload images and see the results.

1.5 Significance of the Project

Recognizing brain tumors is critical in healthcare diagnostics due to the severe implications these anomalies can pose to patients' health and overall quality of life. Tumors pose a considerable challenge because of their extensive connections to neurons and supportive tissues, making the brain susceptible to various illnesses. These tumors, which are marked by irregular cell growth within brain tissue, can impact individuals regardless of age or background and come in multiple forms, from benign to malignant. Given that brain tumors can interfere with neurological functions and result in symptoms such as headaches, seizures, cognitive decline, and life-threatening complications, prompt and precise identification is essential. Furthermore, the timing of diagnosing these conditions is crucial in shaping the prognosis and treatment options accessible to those diagnosed with brain tumors. Early identification increases the chances of favorable treatment outcomes, enabling healthcare professionals to adopt approaches aimed at maintaining quality of life and cognitive functions.

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1.6 Project Risks Assessment

The potential risks associated with this project include:

Table 1.1 Risks Assessment

Risks	Mitigation Strategy
The model may be trained and perform poorly due to the lack of full quality MRI image datasets available	Utilize public datasets and augment to increase size and diversity.
The model has the risk of not achieving the desired accuracy. Missed tumours or incorrect detection of tumours may cause low accuracy	Optimize model architecture and use data augmentation and hyper parameter tuning.
Limited computational resources	Access higher capacity computer

1.7 Project Organization

In this document, we will outline the activities and processes that played a role in the design and implementation of this project. The following chapters will cover the specific topics listed below:

Chapter 2: Literature Review - This section reviews relevant literature related to the Detection of Brain Tumors through machine learning.

Chapter 3: Methodology - This chapter will detail the tools, techniques, and frameworks employed in the project's development, including system architecture, workflow, and system requirements, among other aspects.

Chapter 4: Implementation and Testing - This chapter provides an overview of the algorithm development process in detail.

Chapter 5: Conclusion - This section wraps up the project, emphasizing areas for potential improvement and key findings.

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CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter will explore the innovative frameworks that integrate advanced techniques such as Convolutional Neural Networks (CNNs). By examining recent advancements in deep learning and feature extraction methods, this chapter aims to provide a comprehensive overview of the present landscape of brain tumor detection, emphasizing how these technologies can significantly improve clinical outcomes and patient care.

2.2 Historical Overview

Historically, the detection of brain tumors has largely relied on conventional imaging methods such as computed tomography (CT) and magnetic resonance imaging (MRI). While these techniques have revolutionized diagnostic neuroimaging by offering outstanding clarity in visualizing anatomical structures, their ability to identify subtle or early-stage abnormalities remains limited. Additionally, interpreting the results of imaging usually necessitates the expertise of radiologists or neurosurgeons, which can result in delays in both diagnosis and the initiation of treatment. In recent years, technological innovations and computational techniques have led to the development of new approaches for identifying brain tumors. Machine learning algorithms have surfaced as powerful tools for analyzing medical imaging data and deriving clinically significant insights with remarkable precision and efficiency. By leveraging large datasets of annotated images, these algorithms can be trained to detect patterns associated with brain tumors, thereby facilitating automated screening and detection processes that enhance healthcare providers' capabilities. Convolutional neural networks (CNNs), a recent advancement in deep learning algorithms geared specifically toward image-related tasks, exemplify the applicability of machine learning in diagnosing brain tumors. These networks are adept at segmenting basic shapes, relationships, and intricate patterns within medical images, enabling the distinction between healthy and pathological brain areas. By utilizing various CNN models, they can pinpoint subtle changes in image intensity, shape, or texture that may suggest the presence of a tumor through an iterative training process using labeled datasets.

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Deep learning, which falls under the umbrella of artificial intelligence, has become a powerful tool in medical imaging, particularly for brain segmentation. Brain segmentation is a critical component of medical diagnostics and research, allowing for precise delineation of both anatomical structures and pathological areas in brain images. Traditional methods for segmentation, often relying on manual labeling or standard image processing techniques, can be labor-intensive and prone to variability. In contrast, deep learning approaches capitalize on large datasets and advanced neural network architectures to automate and enhance the segmentation process, attaining high levels of accuracy and consistency. Convolutional neural networks (CNNs) have demonstrated significant success in capturing complex features and patterns in brain images, facilitating the detection of subtle distinctions between healthy and diseased tissues.

Recent advancements in deep learning have improved brain segmentation techniques by incorporating innovative architectures such as U-Net, Fully Convolutional Networks (FCNs), and Transformer models. These models are specifically designed to address the intricate and varied nature of brain structures, offering superior performance compared to traditional methods. The application of deep learning in brain segmentation not only boosts diagnostic accuracy and treatment planning but also accelerates research progress in neuroscience and related fields. Additionally, the advent of transfer learning and domain adaptation techniques allows for the effective utilization of pre-trained models, reducing the necessity for extensive labeled datasets and permitting more efficient applications in clinical settings. As deep learning continues to develop, its potential to reshape brain segmentation and broader medical imaging applications becomes ever more apparent.

2.3 Related Works

The study by Hollon et al. (2018) represents a significant advancement in the intraoperative detection of pediatric brain tumors by utilizing stimulated Raman histology (SRH) in conjunction with machine learning approaches. Achieving a diagnostic accuracy of 100% in identifying tumor types through the analysis of image features from SRH, this research underscores the potential of combining machine learning with novel imaging techniques to improve the precision and effectiveness of brain tumor detection, thereby aiding surgical decision-making. This study not only validates the ability of SRH to preserve crucial histopathological information but also demonstrates the transformative influence of machine learning on medical diagnostics.

The investigation conducted by Reszke (2023) offers a comprehensive analysis of the application of machine learning methods, specifically convolutional neural networks (CNNs), in identifying brain

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tumors using magnetic resonance imaging. The findings showcase the success of various pre-trained models, achieving notable accuracy and performance metrics, which emphasizes the promise of machine learning as a vital tool for clinicians during the initial diagnostic phases. Moreover, it highlights the importance of interpretable machine learning and the need for further research on image detection methods, laying the groundwork for advancements in automated tumor identification and localization.

Khan (2023) provides a thorough exploration of the application of machine learning techniques, particularly ensemble methods, for the early detection of brain tumors via MRI data. The research stresses the significant role of convolutional neural networks in feature extraction, which enhances the classification accuracy of brain tumor images, achieving remarkable results with a detection accuracy of 95.9%. This study underscores the importance of integrating different machine learning models to improve diagnostic accuracy, fulfilling the urgent need for automated strategies in the swift detection of brain tumors, which is crucial for patient survival.

Goyal & Sharma (2023) present a detailed examination of a system designed to detect brain tumors using neural networks, highlighting the effectiveness of deep learning methods in medical imaging. By comparing a standard Convolutional Neural Network (CNN) with a combined CNN-Long Short-Term Memory (LSTM) model, the authors showcase significant improvements in detection accuracy, sensitivity, and specificity, thereby underscoring the groundbreaking potential of machine learning in enhancing diagnostic procedures for brain tumors. This research not only illustrates the practical application of neural networks in healthcare but also emphasizes the importance of accessible datasets in fostering innovation in this field.

Sadad et al. (2021) conduct a thorough analysis of advanced deep learning techniques for the detection and classification of brain tumors, underscoring the crucial role of automated systems in enhancing diagnostic accuracy and efficiency. By employing architectures such as UNet alongside ResNet50 and exploring various convolutional neural networks (CNNs), the study achieves notable improvements in classification accuracy, reaching up to 99.6% with NASNet, thus highlighting the transformative impact of machine learning on brain tumor diagnostics. This research not only showcases the efficacy of transfer learning and data augmentation but also sets a benchmark for future studies focused on automated methods for brain tumor detection.

In their 2023 research, Saeedi et al. provide a comprehensive review of how convolutional deep learning methods can be applied for detecting brain tumors through MRI scans. The authors

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demonstrate the effectiveness of their proposed 2D Convolutional Neural Network (CNN) and convolutional auto-encoder network, attaining impressive accuracy rates of 96.47% and 95.63%, respectively, thereby accentuating the ability of machine learning techniques to enhance the early identification of glioma, meningioma, and pituitary tumors. This study not only illustrates the superior performance of deep learning models over traditional machine learning methods but also emphasizes their practical applicability in clinical settings, making a significant contribution to the field of medical informatics and decision-making in oncology.

Tummala (2023) provides a thorough exploration of advancements made in employing machine learning for the classification of brain tumors, specifically highlighting the efficacy of a deep learning model known as Inception ResNet. The study indicates a significant improvement in diagnostic accuracy, achieving a rate of 96.7% in identifying and categorizing various types of brain tumors from a large dataset of MRI images, thus underscoring the potential of machine learning to enhance early detection and reduce the necessity for invasive diagnostic techniques. The findings presented in this preprint offer important perspectives on ongoing efforts to integrate artificial intelligence into medical imaging, with the primary aim of improving patient outcomes related to malignant brain tumors.

The investigation by Lamrani et al. (2022) delves deeply into the application of convolutional neural networks (CNNs) for identifying and classifying brain tumors using MRI images. Their findings highlight the effectiveness of CNNs in achieving high precision and accuracy levels, showcasing the capability of machine learning techniques to enhance diagnostic procedures in medical imaging. This study not only illustrates the benefits of CNNs over traditional methods but also positions them as a key strategy in the ongoing evolution of brain tumor detection, reinforcing the significant role of artificial intelligence within healthcare.

Wang (2023) provides a comprehensive analysis of advancements in machine learning techniques, particularly focusing on deep learning approaches like convolutional neural networks (CNNs) for the detection and classification of brain tumors in medical imaging. By reviewing results from recent studies conducted between 2020 and 2022, it highlights the effectiveness of various artificial intelligence methodologies, including supervised, reinforcement, and unsupervised learning, thereby illustrating the transformative impact of these technologies on enhancing diagnostic accuracy and clinical outcomes in neuro-oncology.

Birajdar (2023) offers an in-depth investigation of a groundbreaking approach for brain tumor detection utilizing machine learning algorithms, with a particular emphasis on the performance of

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convolutional neural networks (CNNs). The study leverages a diverse dataset of brain MRI scans and stresses the importance of data preprocessing to enhance image quality, which is crucial for increasing classification accuracy across different machine learning methods, such as random forests and support vector machines (SVMs). This research significantly contributes to the growing body of literature on automated medical diagnostics, showcasing the potential of machine learning to improve clinical decision-making in brain tumor identification.

The paper titled "Brain Tumor Detection by Modified Particle Swarm Optimization Algorithm and Multi-Support Vector Machine Classifier" (2022) discusses a novel approach for identifying brain tumors through the integration of advanced machine learning techniques, specifically the Modified Particle Swarm Optimization (MPSO) and Multi-Support Vector Machine (MSVM) classifiers. This research highlights the pressing need for automated solutions in medical imaging, addressing the challenges and time limitations associated with manual tumor segmentation and classification, which ultimately leads to enhanced diagnostic accuracy and improved patient outcomes. The achieved accuracy rate of 98.89% emphasizes the potential of machine learning methodologies in boosting the effectiveness of brain tumor detection, marking a significant advancement in the field of intelligent engineering and systems.

Shrotriya (2023) investigates the application of sophisticated deep learning techniques for brain tumor detection, emphasizing how machine learning can improve both the accuracy and speed of tumor identification in MRI scans. By addressing the limitations of manual classification, this research demonstrates how machine learning can expedite diagnostic processes, thus facilitating timely treatment for patients with brain tumors. This is in line with the overarching goal of enhancing clinical decision-making through innovative technological advancements in healthcare.

Ma (2023) provides a comprehensive examination of machine learning techniques for classifying brain tumors, highlighting the significant enhancements in diagnostic accuracy achieved through automation. By detailing methods such as convolutional neural networks and probabilistic neural networks, the piece showcases these technologies' potential to better clinical decision-making and improve patient outcomes in a medical specialty known for its complexities. Furthermore, the accuracy statistics shared and the analysis of resource use offer valuable perspectives on the real-world implications of integrating machine learning into healthcare settings.

Chauhan et al. (2023) perform an in-depth analysis of various machine learning models employed for detecting brain tumors, stressing the comparative efficacy of methods like K-Nearest Neighbors,

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Decision Trees, and Multi-Layer Perceptron Models. This investigation underscores the importance of evaluating multiple algorithms to determine the most accurate and effective technique for tumor identification, addressing the pressing need for quick and reliable diagnostic solutions in the healthcare sector. By scrutinizing over 250 axial MRI scans, this research provides critical insights into how machine learning can enhance diagnostic precision, ultimately aiming to reduce patient wait times for results.

The research by Manogaran et al. in 2019 illustrates a significant advancement in the automated detection of brain tumors through a machine learning model utilizing orthogonal gamma distribution. Their findings, revealing an outstanding accuracy rate of 99.55%, underscore the capacity of machine learning techniques to refine diagnostic processes in healthcare, particularly in evaluating magnetic resonance imaging (MRI) data for brain-related issues. This study not only addresses the crucial issue of data sample imbalance but also paves the way for further exploration of AI applications in medical diagnostics, highlighting the need for innovative approaches to identify complex health concerns.

Kumar et al. (2019) presents a significant improvement in the automatic detection of brain tumors by integrating Berkeley Wavelet Transformation with Support Vector Machine (SVM) methodologies. This study points out the considerable challenges encountered by traditional detection techniques, such as prolonged processing durations and reliance on clinician expertise, and advocates for the use of supervised machine learning to advance existing literature that supports machine learning applications in medical diagnostics, particularly in accelerating and enhancing the dependability of brain tumor detection.

The study by Brindha and colleagues (2021) highlights the efficacy of deep learning approaches in rapidly and accurately identifying brain tumors within MRI scans. Their findings indicate that these advanced algorithms not only enhance diagnostic accuracy but also facilitate timely treatment interventions, supporting radiologists in making informed clinical decisions. This research significantly contributes to the growing body of literature that endorses the integration of machine learning in medical imaging to improve patient outcomes.

Sutradhar et al. (2021) presents a comprehensive examination of several machine learning methods, including Support Vector Machine, Random Forest, Decision Tree, K-Nearest Neighbor, as well as more sophisticated techniques like Temporal Convolution and Transfer Learning, specifically aimed at identifying brain tumors in MRI scans. The study underscores the significance of automated systems in healthcare to bolster the accuracy and effectiveness of tumor classification, addressing the

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complexities introduced by the diverse shapes and locations of brain tumors. By integrating various methods, the authors offer valuable perspectives on how machine learning can improve diagnostic practices in neuroimaging.

2.4 Comparative Analysis

Table 2.1 Comparative Analysis

Authors	Methodology	Strength	Weakness	Accuracy (%)
Hollon et al. (2018)	Stimulated Raman Histology	Rapid intraoperative diagnosis	Limited to pediatric cases	100
Reszke & Smaga (2023)	Machine learning methods	Comprehensive review of ML techniques	Generalizability issues	Not specified
Khan et al. (2023)	MRI-based ensemble frameworks	Effective predictions with ensemble methods	Requires extensive training data	95.9
Goyal & Sharma (2023)	Neural networks	Simple implementation, good accuracy	Potential overfitting	Not specified
Sadad et al. (2021)	Advanced deep learning techniques	High accuracy and multi-classification	Computationally intensive	99.6
Saeedi et al. (2023)	Convolutional deep learning and machine learning	Combination of DL and ML techniques	Complexity in model selection	96.47
Tummala (2023)	Deep neural networks	Novel approach, good for classification	Limited dataset scope	96.7
Lamrani et al. (2022)	Convolutional neural networks	Effective for MRI image analysis	May require substantial preprocessing	Not specified

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Wang (2023)	Literature review	Comprehensive overview of ML's role	Lack of empirical data	Not specified
Birajdar (2023)	CNN algorithm	Good for feature extraction	May be limited by dataset diversity	Not specified
IJIES (2022)	Swarm intelligence techniques coupled with support vector machine classifiers.	Innovative method combination	Limited by optimization efficiency	98.89
Shrotriya et al. (2023)	Advanced deep learning implementations	High accuracy and adaptability	Complexity in implementation	Not specified
Ma & Lin (2023)	Machine learning techniques	Focus on classification	Limited real-world application	Not specified
Chauhan et al. (2023)	Comparison of machine learning models	Identifies best performing models	Limited scope of comparison	Not specified
Manogaran et al. (2019)	Gamma distribution and machine learning	Effective handling of data imbalance	Requires complex preprocessing	99.55
Kumar et al. (2019)	Automated MRI detection using wavelet transformation and SVM	Automated method improves efficiency	Limited by wavelet transformation accuracy	Not specified
Brindha et al. (2021)	Deep learning techniques	Good performance in MRI images	May require large datasets	

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Sutradhar et al. (2021)	Multi-modal case study with various ML algorithms	Comprehensive approach with multiple algorithms	Complexity in integration of multiple techniques	
Ghemosu & Joshi (2021)	Jaya algorithm and twin SVM	Effective classification	May be limited by Jaya algorithm's applicability	97.89
Sarwar et al. (2022)	Transfer learning application for tumor diagnosis	Utilizes transfer learning effectively	Dependence on pre-trained models	

2.4 Summary

To sum up, the review of existing literature emphasizes the groundbreaking impact of deep learning on systems for detecting brain tumors. The transition from traditional machine learning approaches to deep learning frameworks has significantly enhanced diagnostic accuracy and expanded potential applications in medical imaging. Future research should focus on optimizing algorithms, broadening datasets, and addressing ethical concerns associated with medical data usage. In the next chapter, we will examine the specific requirements and design considerations essential for developing a brain tumor detection system that utilizes deep learning methods.

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CHAPTER THREE

REQUIREMENTS, ANALYSIS AND DESIGN

3.1 Overview

The objective of the project is to utilize cutting-edge machine learning methods, particularly deep learning, to improve the precision and effectiveness of identifying brain tumors from MRI images. This chapter describes the necessities, analysis, and design of the suggested model, clarifying the approaches used, ethical considerations, and criteria for both functional and non-functional requirements.

3.2 Methodology

The Agile methodology fits this project well because of its iterative approach, adaptability, and focus on teamwork. Considering the complexities involved in machine learning projects, Agile enables ongoing improvements and adjustments as the project progresses.
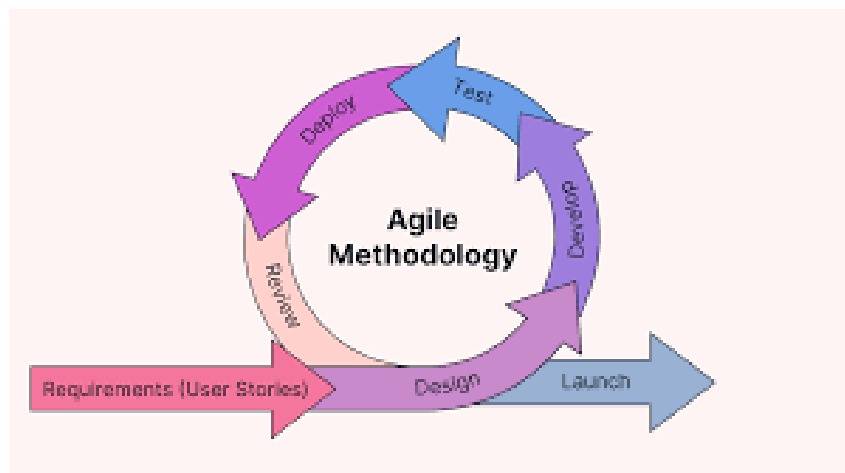
Fig 3.1 Agile Methodology

3.3.1 Interview

1   Conversations were essential to the progress of this project, offering detailed perspectives from healthcare experts. The primary objectives of the interviews for this project include:

2   Understand current practices in brain tumor detection, including existing tools and technologies.

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3   Gather insights on challenges faced by medical professionals, such as limitations of current technologies and areas where machine learning could improve diagnostic processes.

4   Explore user expectations to ensure that the machine learning tool aligns with the needs of healthcare professionals.

3.4 Tools and Techniques

The project utilizes a variety of tools to enhance system development and functionality.

Flask is used for the backend, providing a lightweight web framework to integrate Python with web technologies and create RESTful APIs, which is essential for quick iterations in a research-driven environment.

The user interface is designed using HTML and CSS, providing a straightforward experience for healthcare professionals to interact with the system, upload MRI scans, review results, and access reports.

Kaggle is utilized as the main repository for datasets, supplying high-quality MRI images essential for training and validating the machine learning models.

TensorFlow is used for image processing and training deep learning models, leveraging its capabilities to build and enhance Convolutional Neural Networks (CNNs).

Seaborn and Matplotlib facilitate effective data visualization, showcasing training outcomes and model performance metrics, including confusion matrices and ROC curves.

NumPy is instrumental in managing large multi-dimensional arrays and matrices, assisting in the preprocessing of image data to ensure efficient and effective manipulation for machine learning models.

Dataset used:

The dataset utilized for this project is compiled from three different datasets obtained from Kaggle:

1   Figshare ()
2   SARTAJ dataset()
3   Br35H()

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This collection includes 7,023 MRI images of the human brain, categorized into four classes: glioma, meningioma, no tumor, and pituitary.
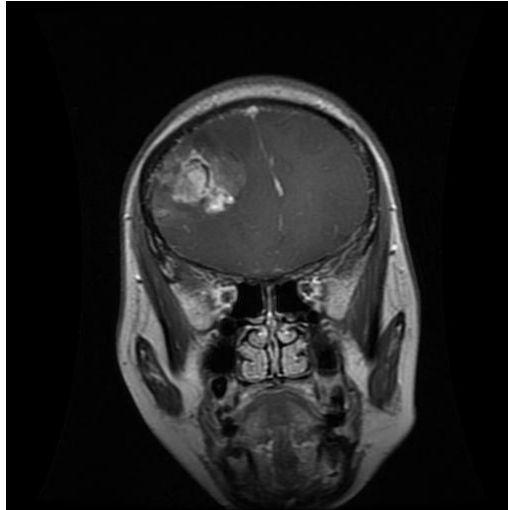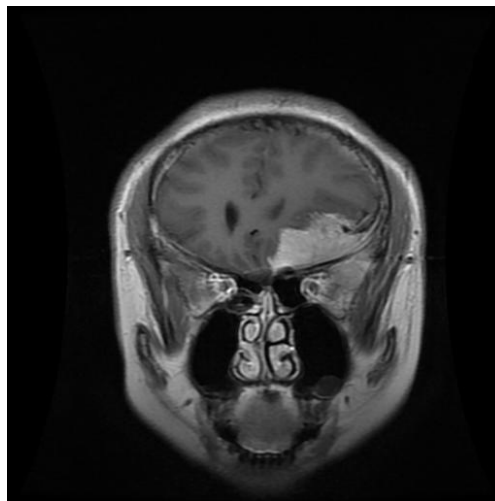

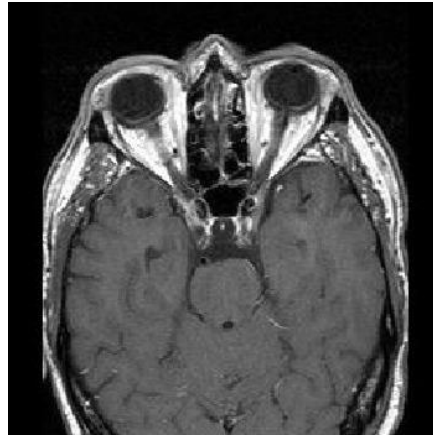*Fig 3.2 Giloma*

Fig 3.3 Meningioma
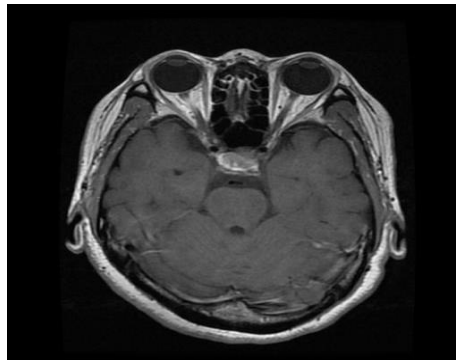
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Fig 3.4 No Tumor

Fig 3.5 Pituitary

Training Techniques

The project starts with preparing the data, organizing MRI images into separate folders for training and testing, categorized by tumor types like glioma, meningioma, and pituitary, in addition to non-tumor samples. To improve the model's robustness, data augmentation methods are utilized through ImageDataGenerator, which implements various transformations such as rotation, flipping, and zooming to artificially increase the dataset and enhance generalization.

At the core of the system lies a deep learning model built as a Sequential model using frameworks like TensorFlow. This model structure comprises several layers, including convolutional layers for extracting features, pooling layers to reduce dimensionality, flatten layers to ready the data for fully connected layers, dropout layers to mitigate overfitting, and dense layers for the ultimate classification.

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Next, the model is compiled with carefully selected optimizers and an appropriate loss function such as categorical cross-entropy. Training is conducted using the fit() and fit_generator() methods, allowing the model to learn from the augmented training data across multiple epochs. Important hyperparameters like batch size, learning rate, and the number of epochs are optimized to reach the best performance. During this process, the model steadily enhances its capability to accurately identify and classify brain tumors from MRI images.

3.5 Ethical Considerations

Ethical factors are crucial in this project, notably because of the sensitive qualities of medical information and the possible consequences of using machine learning technologies in the healthcare sector. This segment highlights the primary ethical challenges that need to be tackled during the entire project lifecycle, ensuring that the project's development aligns with ethical norms and fosters trust among users.

1. The project emphasizes the importance of patient privacy by implementing anonymization of patient information, making sure that all identifying features are eliminated from MRI images and their accompanying metadata to safeguard individual identities.

2. Informed Consent: Obtaining informed consent from participants is crucial when collecting data for research purposes.

3. Bias and Fairness: To mitigate bias in machine learning models, efforts will focus on using diverse datasets that represent various demographics (e.g., age, gender, ethnicity) to ensure fairness in predictions. Additionally, bias assessments will be regularly conducted to evaluate model performance across demographic groups, with adjustments like re-sampling or parameter tuning implemented if biases are detected.

4. Accountability and Transparency: A structured feedback mechanism will allow healthcare professionals to report discrepancies between model predictions and clinical outcomes, ensuring continuous model improvement and maintaining accountability.

5. Impact on Clinical Practice: The system will be integrated into clinical practice through training for healthcare professionals, continuous system performance monitoring, and careful integration into existing workflows to enhance diagnostics without disrupting established practices.

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6. Ethical Use of AI in Healthcare: As artificial intelligence becomes increasingly integrated into healthcare, ethical considerations surrounding its use are still a concern.

3.6 Requirement Analysis

3.6.1 Hardware Requirements

1. i5 intel 8th Gen Processor
2. 8 GB RAM
3. 1 TB Hard Disk
4. 4 GB Nvidia GPU
5. Monitor

3.6.2 Software Requirements

1. Windows 10
2. Web Browser
3. Python Package Manager
4. IDE (Visual Studio)

3.7 Requirements Specifications

3.7.1 Functional Requirements

Table 3.1 Functional Requirements

Requirement Number	Description
FR-1	The system should process MRI and CT images to identify potential brain tumors.
FR-2	The model should detect and classify tumors into categories (e.g., benign, malignant).

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Requirement Number	Description
FR-3	The system must provide an easy-to-use interface for healthcare professionals to submit images and access outcomes.
FR-4	The system should generate comprehensive reports detailing findings, including images and annotations.

3.7.2 Non Functional Requirements

Table 3.2 Non-Functional Requirements

Requirement Number	Description
NFR-1	The system should ensure high availability, with uptime of 99.9% to support continuous clinical use.
NFR-2	The system should process images and provide results within 5 minutes to meet clinical needs.
NFR-3	The interface of the system should be user-friendly, enabling users to easily navigate and use the system with little to no training required.
NFR-4	The system must adhere to data protection laws to maintain patient confidentiality.
NFR-5	The system should maintain a response time of less than 2 seconds for user interactions.
NFR-6	The system needs to be able to grow in capacity to accommodate larger data sizes as more images are dealt with.

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Requirement Number	Description
NFR-7	The system needs to maintain comprehensive records of all interactions to ensure auditing and compliance.
NFR-9	The model should ensure high accuracy rates (above 90%) in tumor detection across diverse datasets.

3.8 System Design

The system design for this model is structured to provide a seamless integration of various components that work together for accurate tumor detection. Together, these components form an integrated system designed to assist healthcare professionals in detecting brain tumors with high accuracy, while ensuring that the system remains user-friendly and reliable for clinical use.

3.8.1 System Architecture
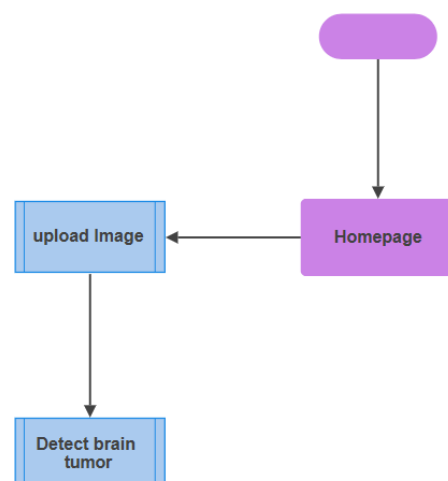
Fig 3.6 System Architecture

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3.8.2 Use Case
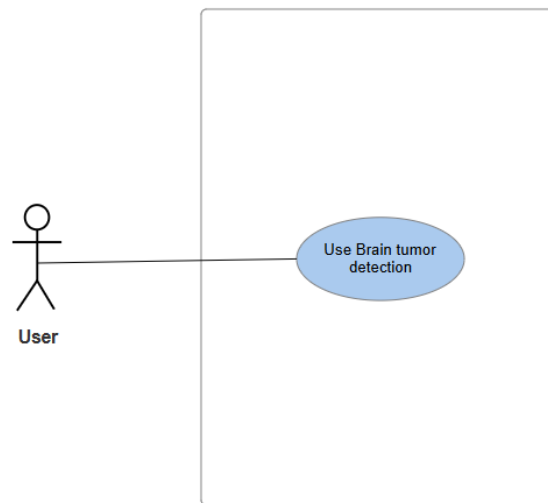
Fig 3.7 Use Case diagram

Use Case: Brain Tumor Detection

Table 3.3 Use case description

Attribute	Description
Use Case Name	Brain Tumor Detection
Description	This use case outlines the process by which the system identifies a brain tumor from an MRI image that has been uploaded, employing machine learning models.
Actors	- User: Medical professionals or patients uploading MRI images for tumor detection. - System: Machine learning model integrated into the web app for brain tumor detection.
Preconditions	1. The user must be logged into the web application. 2. The user has an MRI image of the brain available for upload. 3. The machine learning model is deployed and integrated with the system.
Postconditions	The system displays the result of the tumor detection, including whether a tumor is present and the type of tumor (if applicable).
Main Flow	**User**: 1. The scenario starts when the user submits a brain MRI image to the system.
System	1. The system processes the uploaded MRI image using the pre-trained machine learning model.

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Attribute	Description
	2. The system analyzes the image to detect any tumors present. 3. The system provides the detection results, including whether a tumor is present, and classification. 4. The system displays the result on the user interface, along with confidence levels.
Exception Condition	**"No Tumor Detected"**: If no tumor is detected in the MRI image, the system displays a message: "No tumor detected in the MRI image." **"Error in Detection"**: If the system fails to process the image or encounters an error, it displays an error message: "Error in tumor detection. Please upload a valid MRI image."
Alternative Flow	1. If the MRI image provided is in an incorrect format, the system will ask the user to upload a valid image file (such as JPG or PNG). 2. If the system fails to identify any tumors, the user has the option to upload another image or seek further evaluation from a medical professional.

3.8.3 Dataflow Diagram
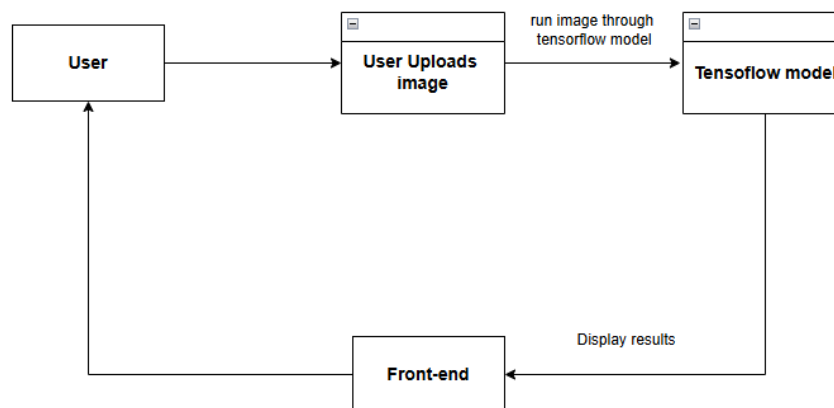
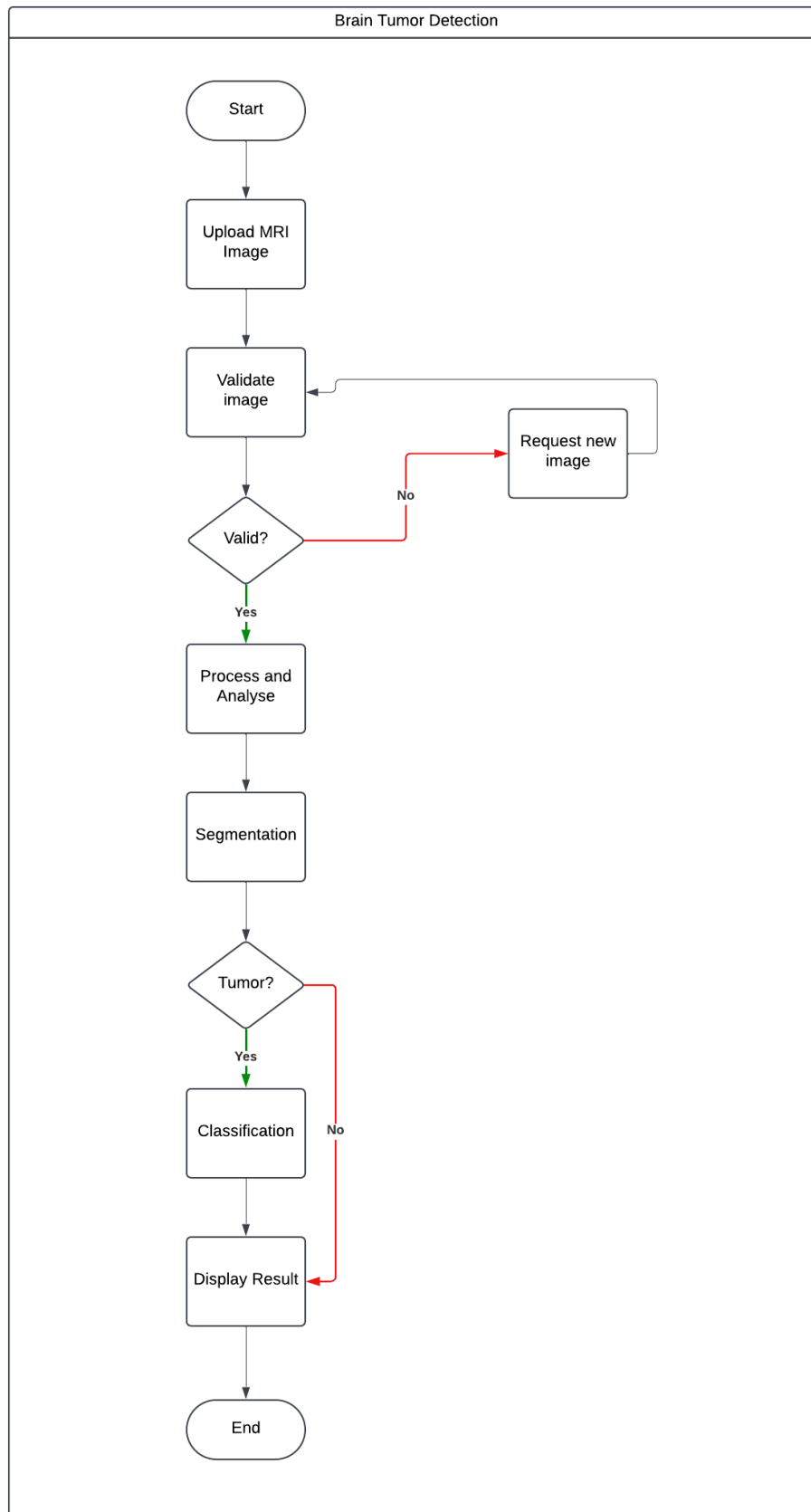

Fig 3.8 Data flow diagram

3.8.4 Activity Diagram:

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Fig 3.9 Activity diagram
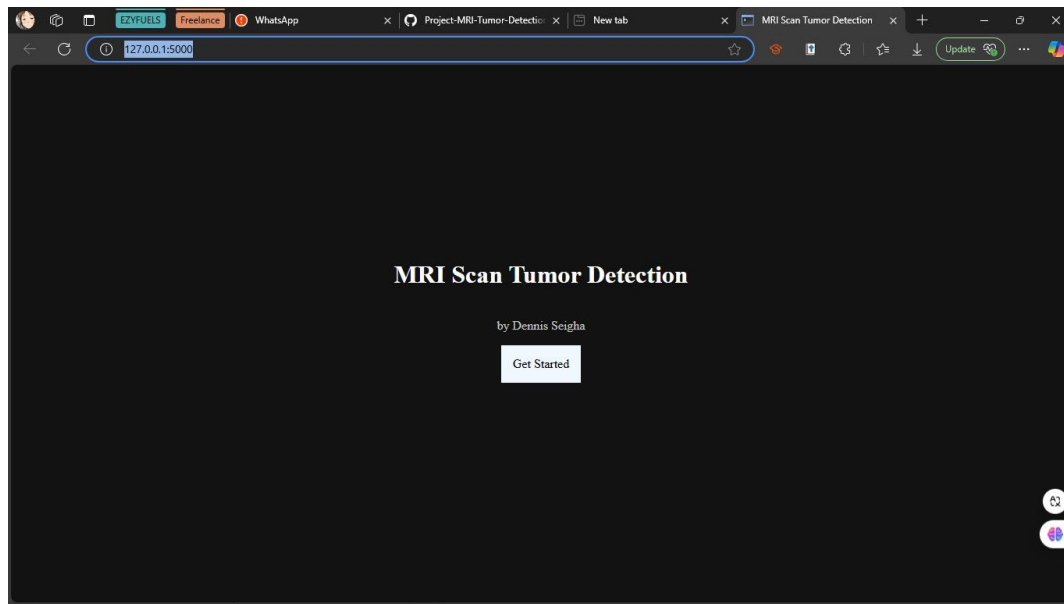
24

3.8.5 User Interface
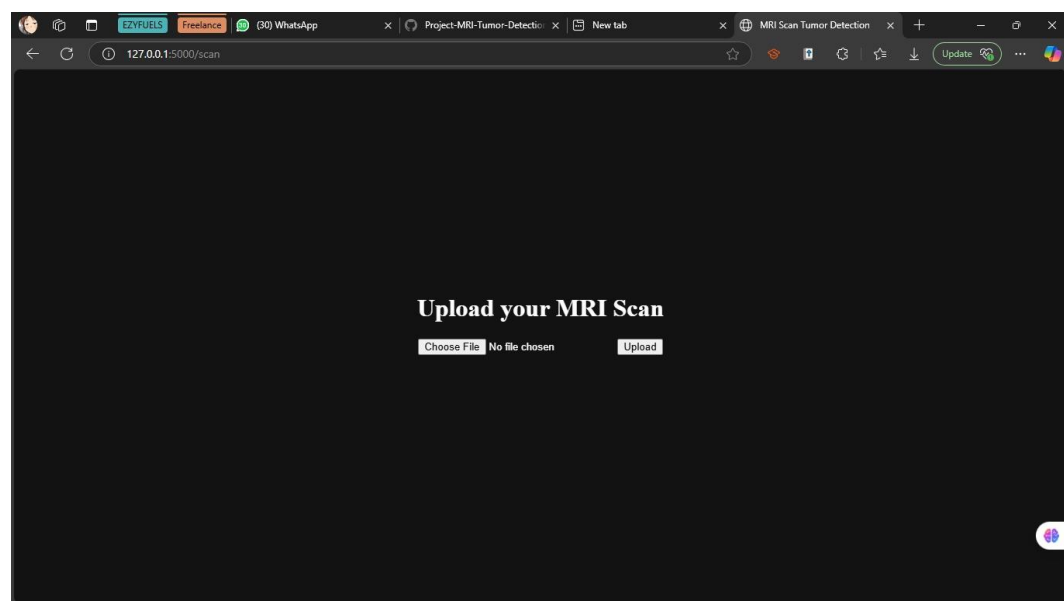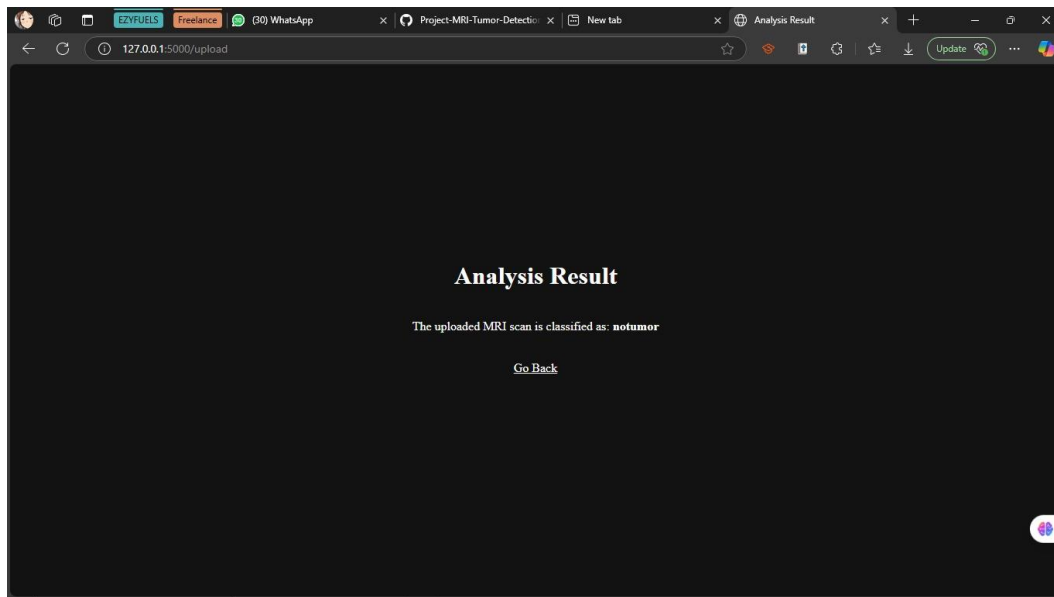

Fig 3.10 UI 1

Fig 3.11 UI 2

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Fig 3.12 UI 2

CHAPTER FOUR

IMPLEMENTATION AND TESTING

4.1 Overview

The implementation stage of the Brain Tumor Detection Using Machine Learning project focused on converting the design specifications into a working system. This stage encompassed data preparation, model creation, training, and incorporating a user-friendly interface. The testing phase thoroughly assessed the system's performance, precision, and usability to confirm it aligned with the project's goals, along with providing a user guide on utilizing the system.

4.2 Main Features

1. Image Processing and Enhancement:
    -   The project used Implemented advanced preprocessing techniques to improve MRI image quality.
    -   Utilized contrast enhancement and noise reduction algorithms to highlight tumor regions.
2. Deep Learning Model:

    • Designed a convolutional neural network (CNN) framework tailored for the detection of brain tumors.

3. Multi-class Classification:

    • Facilitated the system's ability to categorize tumors into various types (e.g., glioma, meningioma, pituitary).User Interface:

    -   Created an intuitive web-based interface for clinicians to upload MRI scans and view results.
    -   Integrated visualization tools to highlight detected tumor regions on the original image.

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4.3 IMPLEMENTATION PROBLEMS

1. Data Scarcity and Imbalance:
   - Limited availability of high-quality, labeled MRI datasets for rare tumor types.
   - Uneven distribution of samples across different tumor categories.
2. Integration Challenges:
   - Difficulties in seamlessly integrating the machine learning model with the user interface.

4.4 Overcoming Implementation Problems

1. Addressing Data Issues:
   - We gathered dataset from multiple sources
   - We applied data augmentation methods to artificially increase the size of the dataset.
   - Utilized transfer learning to leverage knowledge from larger, related datasets.

4.5 TESTING

The test plans for the brain tumor detection system utilizing machine learning detail the testing objectives and designate the essential components that need assessment. The main aim is to verify that all important features, including image preprocessing, tumor identification, and classification, are properly integrated and that the application operates as a unified whole.

4.5.1 Test Plans

Table 4.1 Test cases summary

Test Type	Test Case	Description	Input	Process	Expected Output	Assertion
Unit Testing	Model Prediction	Validate tumor classification	Pre-processed MRI image of known tumor	Feed image to trained model	Correct tumor classification	Predicted class matches known type

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Integration Testing	Image Processing Pipeline	Test end-to-end workflow	Raw MRI image file	Preprocess → Model prediction	Predicted Result	Each step executes without errors, final result accurate
Integration Testing	UI-Backend Integration	Verify user upload and result display	User uploads image via web interface	Frontend → Backend processing → Frontend display	Results displayed on UI	Correct results shown within 10 seconds of upload
System Testing	Accuracy Evaluation	Measure overall system accuracy	Large, diverse test dataset (500+ images)	Process entire dataset through system	High accuracy across all tumor types	Overall accuracy > 95%, F1-score > 0.90 for each class
System Testing	Cross-platform Compatibility	Check system on different browsers/devices	Utilize the system through Chrome, Firefox, or Safari on both desktop.	Perform standard workflow on each platform	Consistent functionality across platforms	All features work correctly on each tested platform

4.6 Results

After system testing was done which included using a variety of new MRI images and it performed well, the following results were collated;

Accuracy: The accuracy ranged from 90% to 100% for the training set and between 85% and 90% for the validation set, as illustrated below:
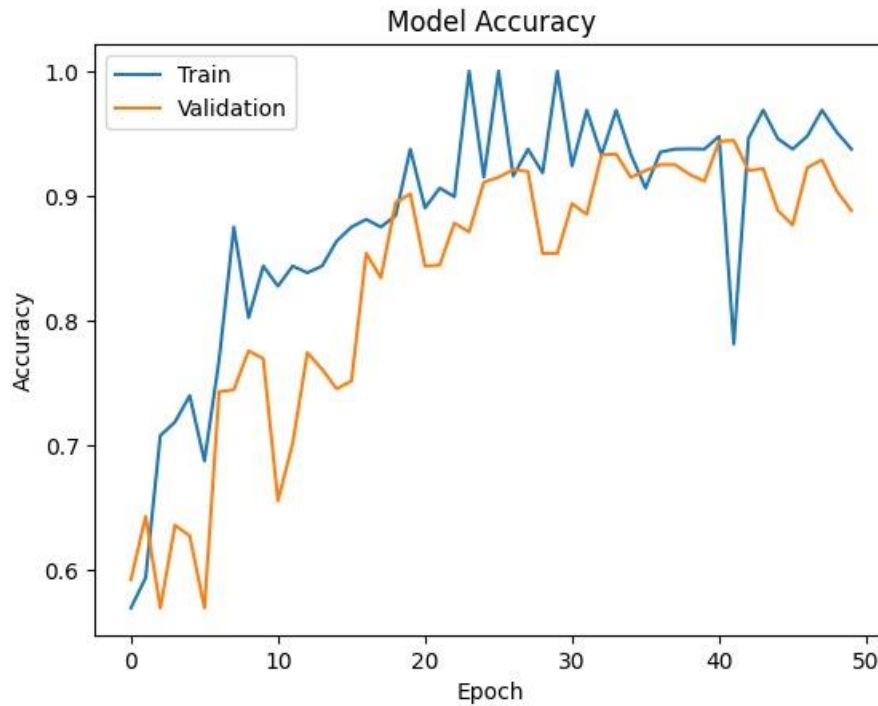
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Fig 4.1 Model Accuracy

Model Loss: The Training loss was just below 0.2 and the Validation loss around 0.3 as shown below.
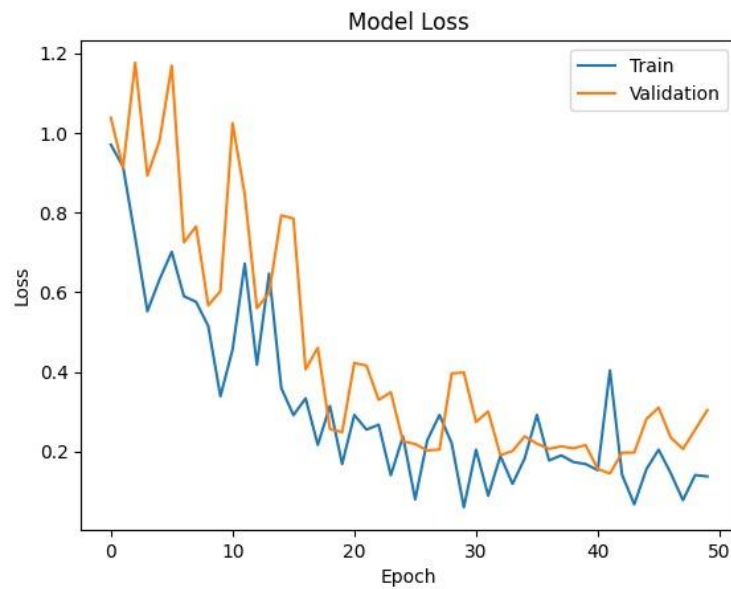

Fig 4.2 Model Loss

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Confusion Matrix: The model performs well overall, particularly in the notumor category, with 403 true positives and minimal misclassification, as only 2 instances are predicted as glioma. Glioma and pituitary tumors are also classified effectively, with few misclassifications. However, the model struggles most with meningioma, where it is often confused with other tumor types, particularly glioma and notumor. Additionally, there are some false negatives for meningiomas (52) and pituitary tumors (2), indicating that there is potential for better accuracy in identifying these categories.
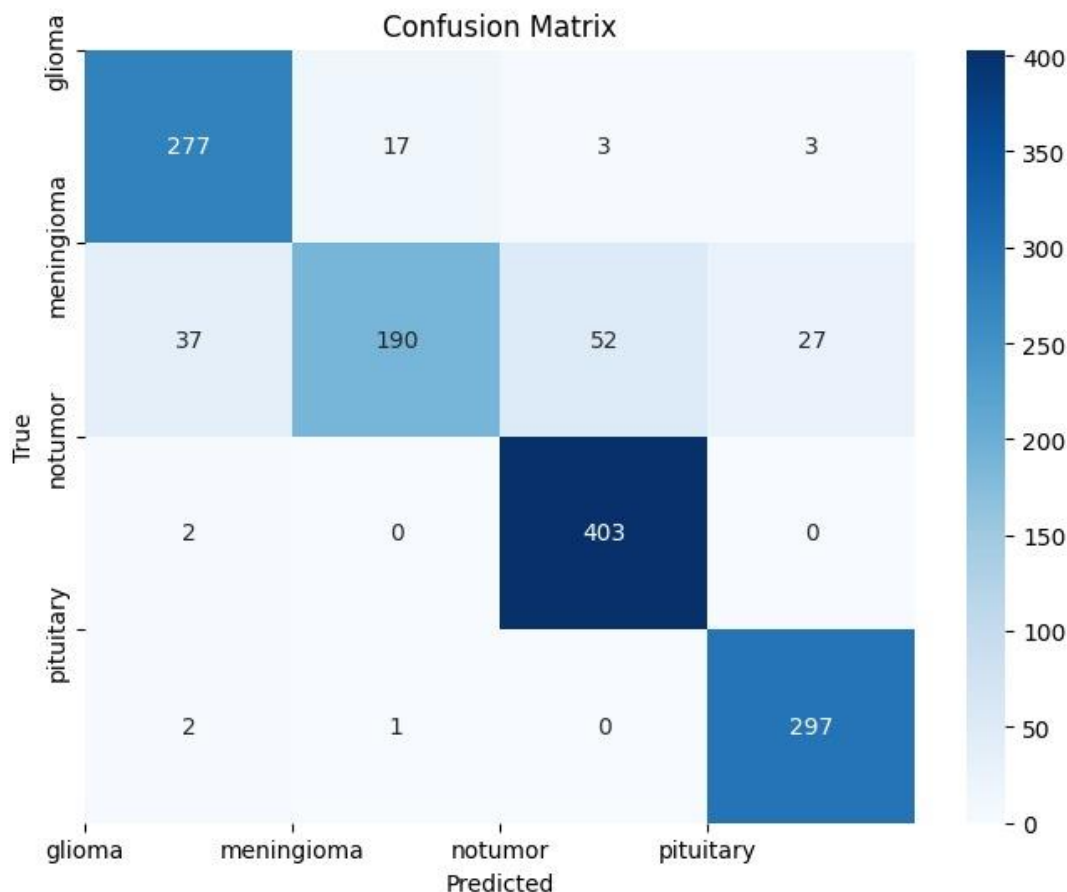

Fig 4.3 confusion matrix

For the Recall, Precision and F1scores;

Table 4.1 Model scores

Class	Precision (%)	Recall (%)	F1-Score (%)
Glioma	87.11	92.33	89.64

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Class	Precision (%)	Recall (%)	F1-Score (%)
Meningioma	91.35	62.09	73.93
No Tumor	87.99	99.51	93.40
Pituitary	90.83	99.00	94.74

4.7 User Guide

1. Accessing the Web Application:

- Open the web application in your preferred browser by visiting the provided URL.

2. Uploading MRI Images:

    i. **Home Screen**:

- The home screen will display a simple interface for uploading your MRI images for analysis.
  ii. **Upload Image**:
- Click the **Upload Image** button on the home page.
- Select the MRI image file from your computer. Supported formats: JPG, PNG, and DICOM.
  iii. **Upload**:
- After selecting your image, click the **Upload** button to start the analysis process.

3. Viewing the Analysis Results:

- Once the image is uploaded, the model will analyze the MRI scan and return a classification.
- The result will show whether the image is classified as:
  - **Glioma**
  - **Meningioma**
  - **Pituitary Tumor**
  - **No Tumor**

3. **Repeat the Process:** You can upload additional MRI images by returning to the **Home Screen** and repeating the upload process.

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4.8 Summary

This chapter has tackled significant challenges faced during the creation and integration of the AI-driven brain tumor detection system utilizing machine learning. The system underwent several revisions to satisfy both functional and non-functional criteria, guaranteeing dependable performance in identifying and classifying brain tumors from MRI scans. Evaluations were performed to assess the accuracy of the model's predictions, specifically in tumor classification. Solutions were devised to ensure that the system addresses the requirements of healthcare providers, emphasizing usability, precision, and the real-time processing of medical images. The system is now well-positioned to offer valuable support in the diagnosis of brain tumors, with the potential for wider implementation in healthcare environments.

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CHAPTER FIVE

DISCUSSIONS AND RECOMMENDATIONS

5.1 OVERVIEW

This chapter presents a comprehensive evaluation of the outcomes from the brain tumor detection initiative, examining the objectives achieved, identifying the limitations and challenges faced throughout the process, proposing possible enhancements, and offering suggestions for further research and development. The insights gained from this project contribute to the continuous efforts to improve diagnostic accuracy and efficiency in clinical settings.

5.2 OBJECTIVE ASSESSMENT

The main goals of this project were to create a machine learning-based system that can effectively identify and categorize brain tumors using MRI scans. The system accomplished impressive accuracy levels across various tumor classifications, showcasing efficient preprocessing methods and strong model performance. Essential performance indicators like precision, recall, and F1-score suggest that the system can consistently support healthcare professionals in diagnosing brain tumors, thereby improving decision-making in the medical field.

5.3 LIMITATIONS AND CHALLENGES

Although this project achieved several successes, it faced a number of limitations and challenges.

1. **Data Limitations**: The availability of high-quality, labeled datasets for rare tumor types was limited.
2. **Model Complexity**: The deep learning model's complexity required significant computational resources for training and inference, which could be a barrier in resource-constrained environments.
3. **Integration Issues**: Initial plans for a mobile application faced compatibility issues with the model format, leading to a shift toward a web-based solution.

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4. **Overfitting Risks**: Although measures were taken to mitigate overfitting, there remains a risk that the model may not perform well on unseen data.

5.4 FUTURE ENHANCEMENTS

To tackle the identified limitations and enhance the system's functionalities, some upgrades are suggested:

1. **Data Augmentation**: Implement more sophisticated data augmentation techniques to artificially expand the dataset and improve model robustness.
2. **Transfer Learning**: Explore additional transfer learning strategies using larger pre-trained models to enhance detection accuracy for rare tumor types.
3. **Real-Time Processing**: Develop optimizations for real-time image processing to facilitate immediate diagnostic feedback in clinical settings.
4. **User Interface Improvements**: Enhance the user interface for better usability and accessibility for clinicians.

5.5 RECOMMENDATIONS

Based on the findings from this project, the following recommendations are proposed:

1. **Collaborative Data Sharing**: Encourage collaboration among medical institutions to create larger, more diverse datasets that can improve model training and validation.
2. **Continuous Model Training**: Establish protocols for continuous model training with new data to adapt to evolving diagnostic needs and improve accuracy over time.
3. **Integration with Clinical Workflows**: Work closely with healthcare professionals to ensure that the system integrates seamlessly into existing clinical workflows, enhancing adoption rates.

5.6 SUMMARY

To conclude, this chapter has outlined the positive results of the brain tumor detection initiative while recognizing its constraints and obstacles. The initiative has shown that machine learning can play a crucial role in identifying brain tumors from MRI scans, offering a beneficial resource for healthcare

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professionals. Suggested improvements and future recommendations focused on enhancing data quality, model efficacy, and user engagement will help progress this significant field of medical technology.

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Appendix A - Project Document

IN-DEPTH PROJECT DOCUMENTATION

Full Candidate Name: Seigha Dennis Junior

Student ID: BU/22A/IT/6599

Title: Design And Implementation Of A Brain Tumors Detection System Using Machine Learning

Course of Study: B.Sc. Computer Science.

Background and Motivation

The brain serves as the central command of the human body, and in recent years, a variety of brain disorders have been identified. The tools for diagnosing brain diseases are becoming increasingly complex and remain a significant area for further research; however, the use of AI in diagnosing brain disorders has enhanced the precision and accuracy of disease prediction and identification. Automated methods for the non-invasive examination of brain images have become essential, as brain diseases are often life-threatening and are a major cause of mortality in developed nations. The integration of AI in brain tumor surgery can lead to safer and more effective treatment outcomes. A notable challenge remains the knowledge gap between clinical professionals and data science experts. This project originates from a need for a tool capable of automatically, scalably and cost effectively helping radiologists to detect brain tumors more precisely and in a timely manner resulting in improved patient outcome.

Statement of the Problem

The problem statement of this work highlights several critical issues in the detection of brain tumors using MRI scans. First, the accuracy of brain tumor detection is compromised due to the reliance on physicians to manually identify tumors, which not only affects detection accuracy but is also a time-consuming process. Second, tumor segmentation presents significant challenges because of the complex nature of brain structures, making it difficult to delineate tumor boundaries accurately. Finally, the primary challenge lies in identifying brain tumors amidst variations in tumor location, shape, size, and intensity across different patients, coupled with the often unclear and irregular boundaries of the tumors. These factors collectively underscore the need for advanced automated solutions to enhance diagnostic accuracy and efficiency in clinical practice.

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Appendix B- Source Codes

```python
from flask import Flask, render_template, request, jsonify, redirect, url_for, flash
from werkzeug.utils import secure_filename
import os
from PIL import Image
import numpy as np
import tensorflow as tf

app = Flask(__name__)

UPLOAD_FOLDER = 'uploads'
os.makedirs(UPLOAD_FOLDER, exist_ok=True)
app.config['UPLOAD_FOLDER'] = UPLOAD_FOLDER
app.config['SECRET_KEY'] = os.urandom(12)
ALLOWED_EXTENSIONS = {'jpeg', 'jpg', 'png'}

def allowed_file(filename):
    return '.' in filename and filename.rsplit('.', 1)[1].lower() in ALLOWED_EXTENSIONS

# Load the pretrained model
model = tf.keras.models.load_model("model/brain_tumor_detection_model.h5")  # Replace with your model path
CLASS_NAMES = ['glioma', 'meningioma', 'notumor', 'pituitary']  # Replace with your tumor class names
print(model.input_shape)
@app.route('/')
def index():
    return render_template("index.html")

@app.route('/scan')
```

```python
    return render_template("index.html")

@app.route('/scan')
def scan():
    return render_template("scan.html")

@app.route('/upload', methods=['POST'])
def upload_file():
    if 'file' not in request.files:
        flash('No file part')
        return redirect(request.url)

    file = request.files['file']
    if file.filename == '':
        flash('No selected file')
        return redirect(request.url)

    if file and allowed_file(file.filename):
        filename = secure_filename(file.filename)
        file_path = os.path.join(app.config['UPLOAD_FOLDER'], filename)
        file.save(file_path)

        # Analyze the image
        result = analyze_image(file_path)

        # Return the result to the frontend
        return render_template("result.html", result=result)
```

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app.py

```python
49
50          # Return the result to the frontend
51          return render_template("result.html", result=result)
52
53      flash('Invalid file type')
54      return redirect(request.url)
55
56      # if 'file' not in request.files:
57      #     flash('No file part')
58      #     return redirect(request.url)
59
60      # file = request.files['file']
61      # if file.filename == '':
62      #     flash('No selected file')
63      #     return redirect(request.url)
64
65      # if file and allowed_file(file.filename):
66      #     filename = secure_filename(file.filename)
67      #     filepath = os.path.join(app.config['UPLOAD_FOLDER'], filename)
68      #     file.save(filepath)
69
70      #     # Analyze the image using the model
71      #     prediction = analyze_image(filepath)
72      #     return render_template("result.html", tumor_type=prediction)
73
74      # return render_template("scan.html")
75
```

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File Edit View Run Tools Help

app.py

```python
76  def analyze_image(image_path):
77      try:
78          # Load the image
79          img = Image.open(image_path).convert("RGB")  # Ensure the image has 3 channels (RGB)
80
81          # Resize to 150x150
82          img = img.resize((150, 150))
83
84          # Convert to NumPy array and normalize pixel values to [0, 1]
85          img_array = np.array(img) / 255.0
86
87          # Add batch dimension to match the input shape (None, 224, 224, 3)
88          img_array = np.expand_dims(img_array, axis=0)
89
90          # Perform prediction
91          predictions = model.predict(img_array)
92          print("Raw predictions", predictions)
93
94          # Get the predicted class
95          predicted_class = CLASS_NAMES[np.argmax(predictions)]  # Map output to class names
96          return predicted_class
97      except Exception as e:
98          print(f"Error analyzing image: {e}")
99          return "Error processing image"
100     try:
101         # Open and preprocess the image
102         img = Image.open(image_path).convert("RGB")  # Convert to RGB if needed
```

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File Edit View Run Tools Help

app.py

```
 96            return predicted_class
 97        except Exception as e:
 98            print(f"Error analyzing image: {e}")
 99            return "Error processing image"
100        try:
101            # Open and preprocess the image
102            img = Image.open(image_path).convert("RGB")  # Convert to RGB if needed
103            img = img.resize((104, 104))  # Resize to match the expected input size
104            img_array = np.array(img) / 255.0  # Normalize pixel values to [0, 1]
105            img_array = np.expand_dims(img_array, axis=0)  # Add batch dimension
106
107            # Predict the tumor type
108            predictions = model.predict(img_array)
109            predicted_class = CLASS_NAMES[np.argmax(predictions)]
110            return predicted_class
111        except Exception as e:
112            print(f"Error analyzing image: {e}")
113            return "Error processing image"
114        # try:
115        # #     # Load and preprocess the image
116        # #     img = Image.open(image_path).convert("RGB")
117        # #     img = img.resize((128, 128))  # Resize to match model input size
118        # #     img_array = np.array(img) / 255.0  # Normalize pixel values
119        # #     img_array = np.expand_dims(img_array, axis=0)  # Add batch dimension
120
121        # #     # Predict the tumor type
122        # #     predictions = model.predict(img_array)
```

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app.py

```
105            img_array = np.expand_dims(img_array, axis=0)  # Add batch dimension
106
107            # Predict the tumor type
108            predictions = model.predict(img_array)
109            predicted_class = CLASS_NAMES[np.argmax(predictions)]
110            return predicted_class
111        except Exception as e:
112            print(f"Error analyzing image: {e}")
113            return "Error processing image"
114        # try:
115        # #     # Load and preprocess the image
116        # #     img = Image.open(image_path).convert("RGB")
117        # #     img = img.resize((128, 128))  # Resize to match model input size
118        # #     img_array = np.array(img) / 255.0  # Normalize pixel values
119        # #     img_array = np.expand_dims(img_array, axis=0)  # Add batch dimension
120
121        # #     # Predict the tumor type
122        # #     predictions = model.predict(img_array)
123        # #     predicted_class = CLASS_NAMES[np.argmax(predictions)]
124        # #     return predicted_class
125        # # except Exception as e:
126        # #     print(f"Error analyzing image: {e}")
127        # #     return "Error processing image"
128
129    if __name__ == '__main__':
130        app.run(debug=True)
131
```

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