A PROJECT REPORT ON

Brain Tumour Detection using CNN

Submitted in Partial fulfilment of Requirements for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

ARTIFICIAL INTELLIGENCE & MACHINE LEARNING

Submitted By

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DEPARTMENT OF CSE(AI&ML)

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2020-2024

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2020-2024

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CERTIFICATE

This is to certify that the project work entitled**, “Brain Tumour Detection using CNN”** is a work carried out by **VAKKALANKA AKHIL (20MH1A4261)**, **GOODUPU VENKATA VAMSI KRISHNA (20MH1A4211), GUBBALA VINAY KUMAR (20MH1A4214), DUDI USHA SREE (20MH1A4258), BOLLINA YUVA SIVA RAMA KRISHNA (20MH1A4205)** in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology in CSE (AI&ML). ADITYA COLLEGE OF ENGINEERING affiliated to JAWAHARLAL NEHRU TECHNOLOGICAL UNIVERSITY KAKINADA is a bonafide work carried out by him/her during the academic year 2023-2024.

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External Examiner

DECLARATION

This is to declare that the project entitled “Brain Tumour Detection using CNN” submitted by us in the partial fulfilment of requirements for the award of the degree of Bachelor of Technology in CSE(AI&ML) in Aditya College of Engineering, is bonafide record of project work carried out by us under the supervision and guidance of Mr K. Ananda Kumar, M. Tech, AMIE (CSE), Assistant Professor, CSE(AI&ML).

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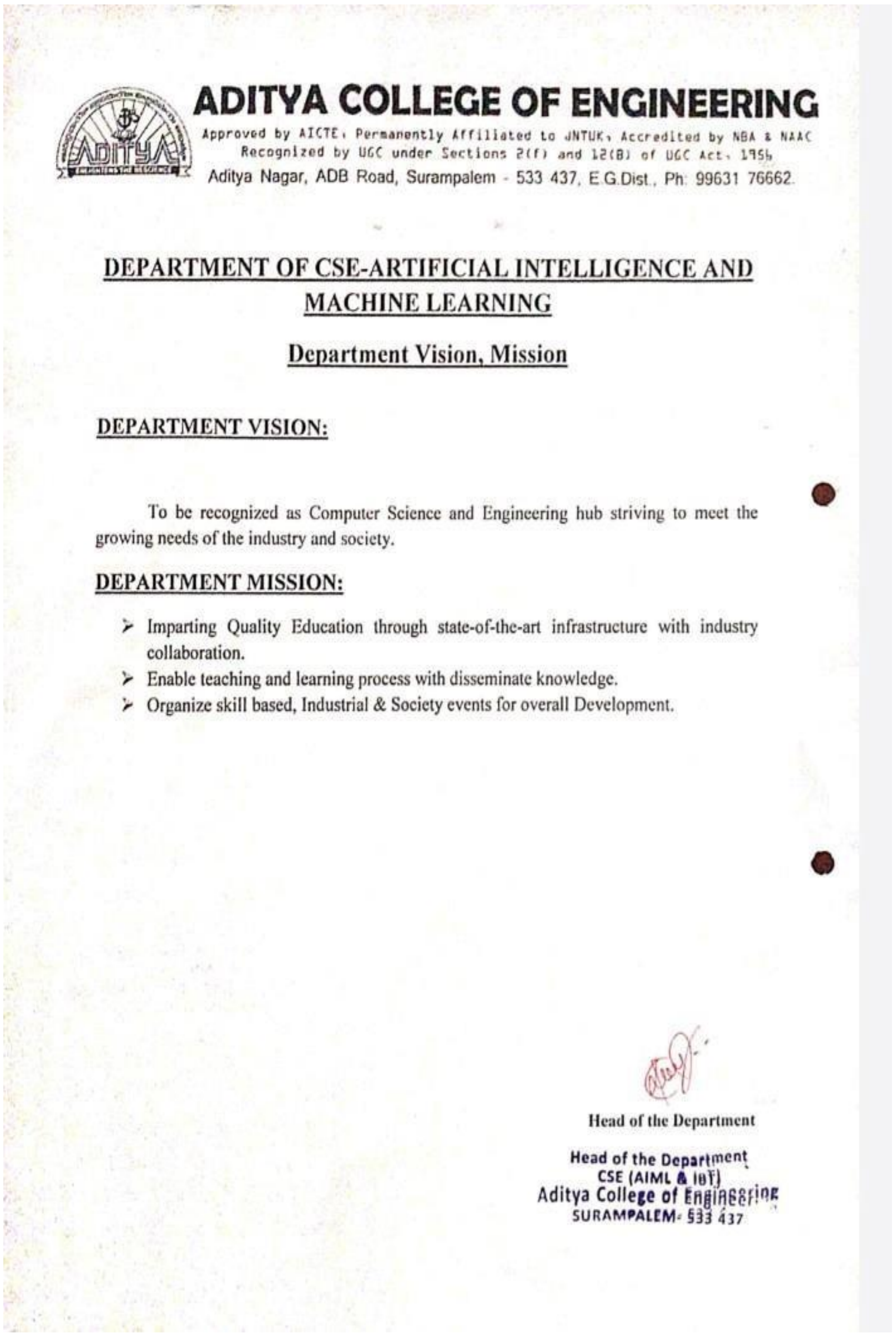

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1. PSO 1: AI and ML System Development

Design, develop, and implement AI and ML systems by applying fundamental principles, algorithms, and techniques.

2. PSO 2: Data-driven Decision-Making

Collect, preprocess, and analyze large and diverse datasets to extract meaningful insights using AI and ML techniques to support data-driven decision-making processes in various domains.

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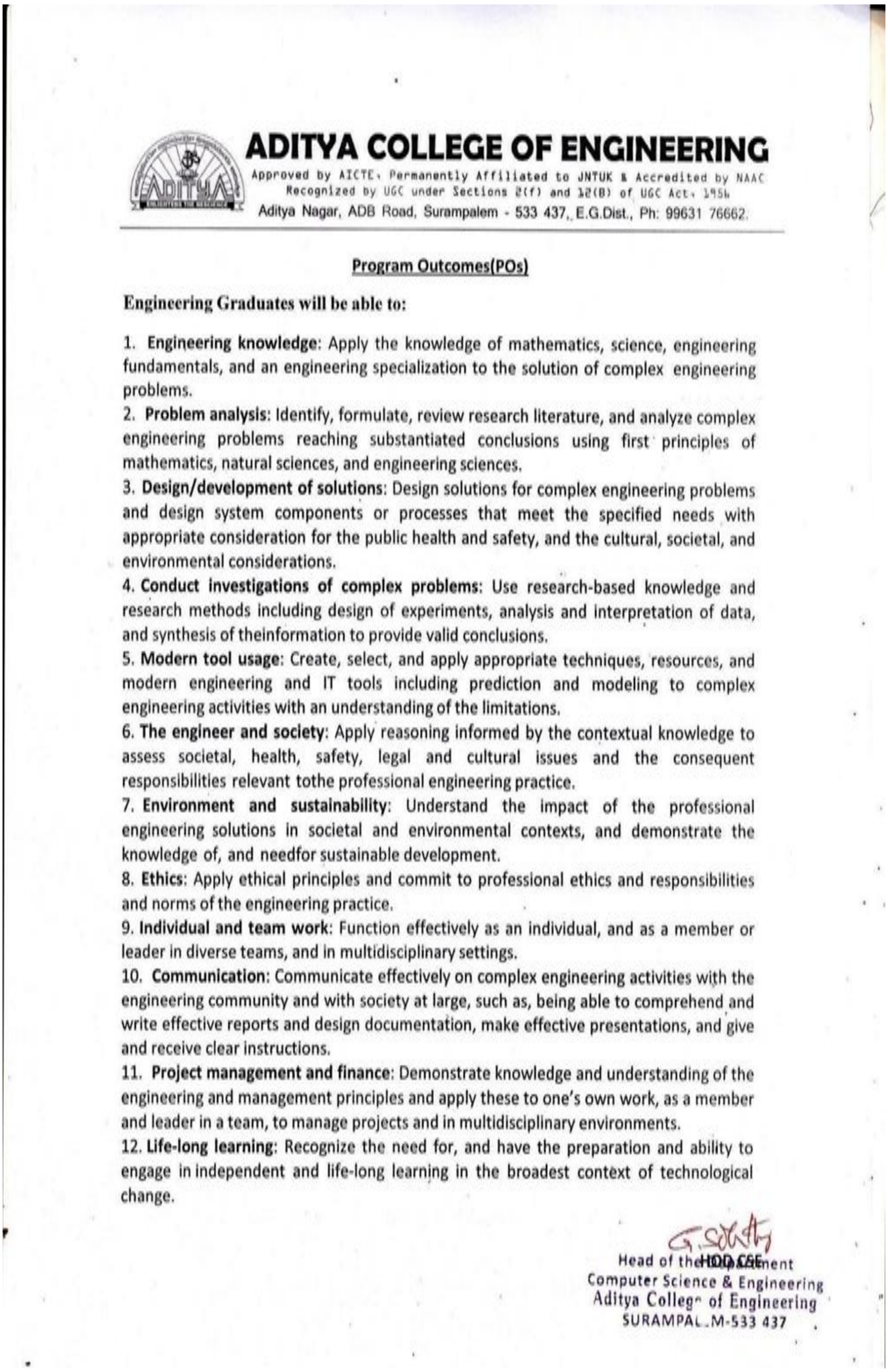

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2. **Problem analysis**: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.
3. **Design/development of solutions**: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.
4. **Conduct investigations of complex problems**: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of theinformation to provide valid conclusions.
5. **Modern tool usage**: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.
6. **The engineer and society**: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant tothe professional engineering practice.
7. **Environment and sustainability**: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and needfor sustainable development.
8. **Ethics**: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
9. **Individual and team work**: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.
10. **Communication**: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.
11. **Project management and finance**: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.
12. **Life-long learning**: Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

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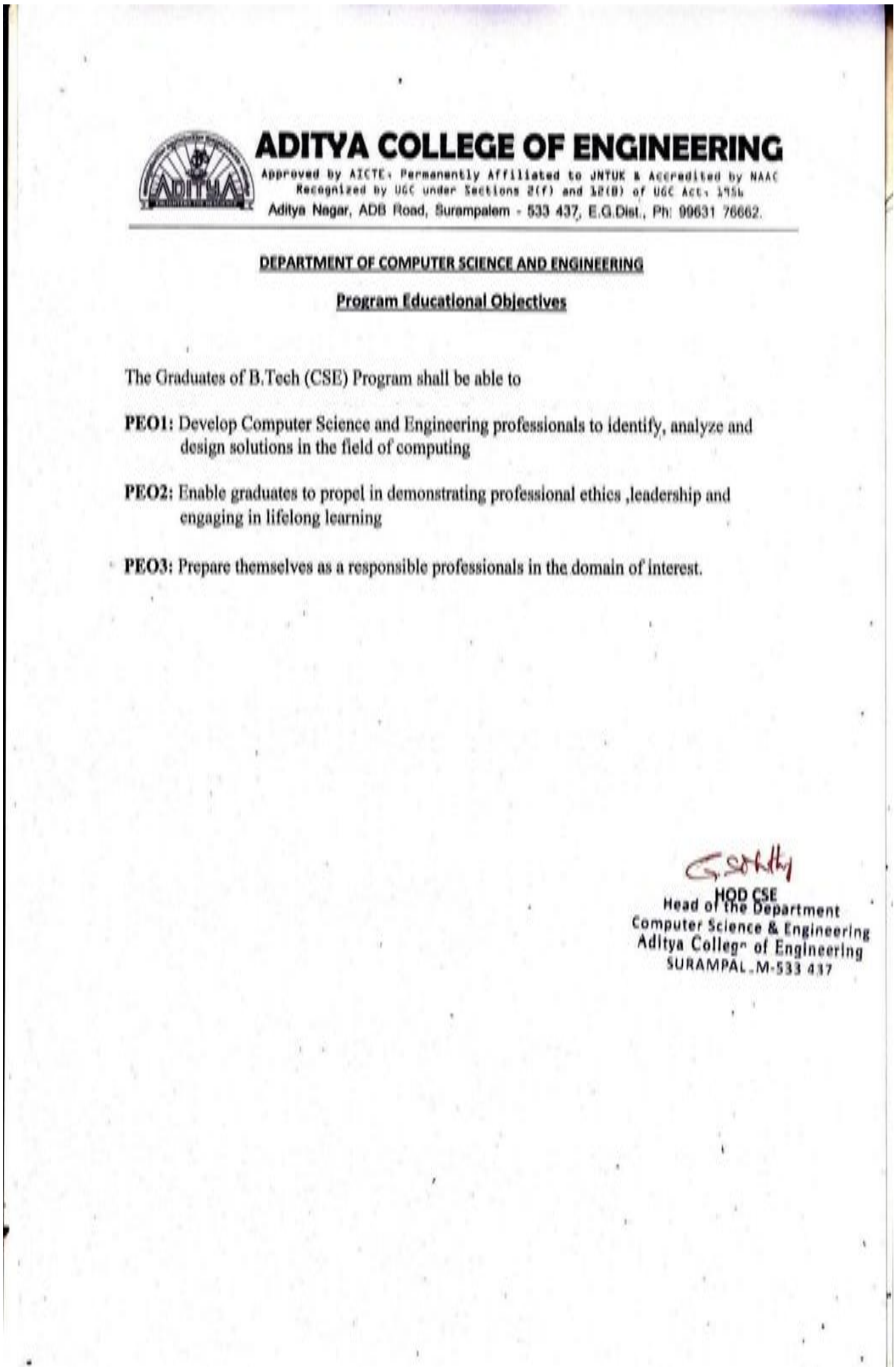

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PEO1: Develop Computer Science and Engineering professionals to identify, analyze and design solutions in the field of computing

PEO2: Enable graduates to propel in demonstrating professional ethics ,leadership and engaging in lifelong learning

PEO3: Prepare themselves as a responsible professionals in the domain of interest.

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Program Educational Objectives(PEO's)

The Graduates of B.Tech (AIML) Program shall be able to:

1. PEO 1: Proficiency in AI & ML Applications

Expertise in designing, developing, and deploying AI and ML solutions for healthcare, finance, and autonomous system problems.

2. PEO 2: Lifelong Learning and Adaptability

Adapt to evolving technologies and industry trends in AI and ML through continuous learning and self-improvement.

3. PEO 3: Effective Communication and Collaboration

Possess strong communication and teamwork skills, enabling them to effectively collaborate with interdisciplinary teams and solve complex problems using AI and ML concepts.

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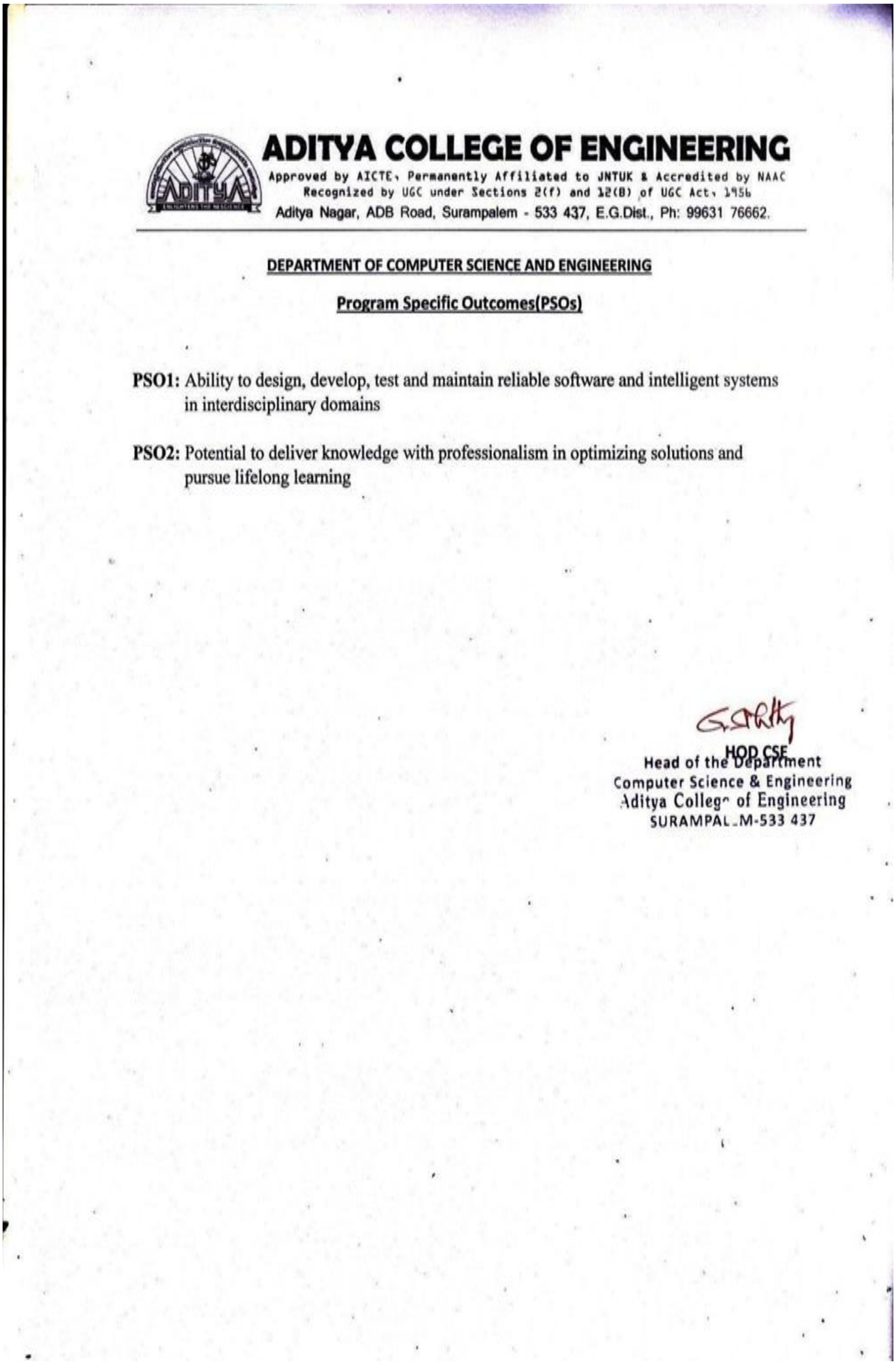

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

Program Specific Outcomes(PSOs)

PSO1: Ability to design, develop, test and maintain reliable software and intelligent systems in interdisciplinary domains

PSO2: Potential to deliver knowledge with professionalism in optimizing solutions and pursue lifelong learning

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Brain Tumor Detection using CNN

ABSTRACT:

A brain tumor is one of the deadliest illnesses which occurs due to the sudden and unregulated brain tissue growth inside the skull. Detection and Classification of a brain tumor is an important step to better understanding its mechanism. However, it is a time taking process and requires expertise to test the MRI images, manually. Nowadays, the advancement of Computer-assisted Diagnosis (CAD), machine learning, and deep learning in specific allow the radiologist to more reliably identify brain tumors. The CAD process has improved dramatically using machine learning (ML) and deep learning (DL) applications in the medical imaging field.

CNN presents a segmentation-free method that eliminates the need for hand-crafted feature extractor techniques. For this reason, different CNN architectures have been proposed by several researchers. Most of the CNN models reported multiclass brain tumor detection, including a vast number of image data. The proposed CNN-based approach not only aims to reduce the time required for diagnosis but also enhances the precision of tumor localization and characterization. This research introduces two deep learning models for identifying brain abnormalities as well as classifying different tumor grades, including meningioma, glioma, and pituitary.

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- Havaei, M., et al. (2017). Brain tumor segmentation with Deep Neural Networks.

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Contents

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ABBREVATIONS

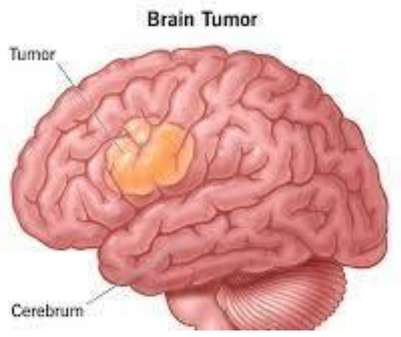
ABBREVATION	FULL FORM
MRI	Magnetic Resonance Imaging
CNN	Convolutional Neural Network
MobileNet	Mobile Convolutional Neural Network
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
RAM	Random Access Memory
GPU	Graphical Processing Unit
SSD	Solid State Drive
API	Application Programming Interface
DSC	Dice Similarity Coefficient
VGG	Visual Geometry Group

Chapter 1

Introduction

Brain Tumor:

A brain tumor is an abnormal growth of cells within the brain or the central spinal canal. Brain tumors can be benign (non-cancerous) or malignant (cancerous), and they can arise from different types of cells in the brain, such as glial cells, meninges, or pituitary gland cells. These tumors can interfere with normal brain function and may cause symptoms such as headaches, seizures, cognitive impairment, and neurological deficits.



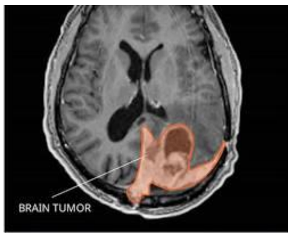
1.i) Brain tumor

Different types of Brain Tumor:

Gliomas: These are the most common type of brain tumor, arising from glial cells, which are supportive cells in the brain. Gliomas can be benign (slow-growing and noncancerous) or malignant (fast-growing and cancerous). The grade of a glioma indicates how aggressive the cancer is. Lower-grade gliomas are slow-growing, while higher-grade gliomas are more aggressive.

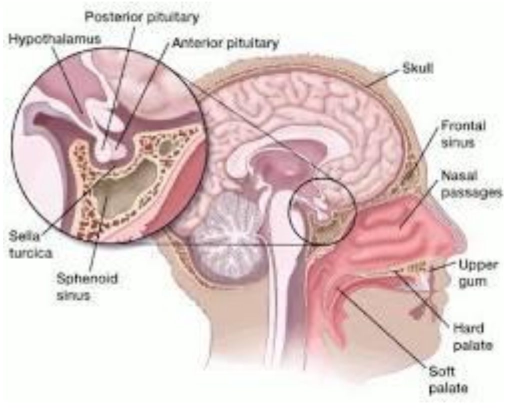
1.ii) Glioma

Meningiomas: These are tumors that form on the meninges, the protective membranes that surround the brain and spinal cord. Meningiomas are usually benign and slow-growing.



1.iii) Meningioma

Pituitary tumors: These tumors develop in the pituitary gland, a small gland at the base of the brain that produces hormones that regulate many essential body functions. Pituitary tumors can be benign or malignant. Benign pituitary tumors can sometimes cause hormonal imbalances due to their size or location.



1.iv) Pituitary

Magnetic Resonance Imaging (MRI):

Magnetic Resonance Imaging (MRI) is a medical imaging technique that uses magnetic fields and radio waves to create detailed images of the body's internal structures, including the brain. MRI is particularly useful for brain tumor detection because it provides high-resolution images that can differentiate between normal brain tissue and abnormal growths. MRI can also help determine the location, size, and characteristics of brain tumors, which is essential for diagnosis and treatment planning.

1.v) MRI

Convolutional Neural Networks (CNNs) for Brain Tumor Detection

Brain tumor detection is a critical task in medical imaging that plays a crucial role in diagnosis and treatment planning. Convolutional Neural Networks (CNNs) have emerged as powerful tools for automated tumor detection from medical images such as MRI (Magnetic Resonance Imaging) scans.

Traditional vs. CNN-based Brain Tumor Detection

In traditional methods, radiologists manually analyse medical images to identify tumors, which is time-consuming and subject to human error. CNNs offer a promising solution by automating this process, providing faster and potentially more accurate tumor detection.

How CNNs Work

CNNs are particularly well-suited for image recognition tasks due to their ability to learn hierarchical features directly from raw pixel data. They consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers, which enable them to automatically extract relevant features from input images.

The Future of Brain Tumor Detection with CNNs:

The development of CNNs holds great promise for improving brain tumor detection. With further research and refinement, CNNs could become even more accurate and efficient in identifying and classifying brain tumors. This could lead to earlier diagnoses, better treatment planning, and ultimately improved patient outcomes.

1.1 Overview

Title: Brain Tumor Detection using Convolutional Neural Networks (CNNs)

Introduction:

Brain tumors are abnormal growths of tissue within the brain or central spinal canal. They can be benign or malignant and can cause various neurological symptoms. Early detection and accurate diagnosis of brain tumors are crucial for effective treatment and patient outcomes. With advancements in machine learning and medical imaging technologies, convolutional neural networks (CNNs) have emerged as powerful tools for automated brain tumor detection and classification from medical imaging data such as magnetic resonance imaging (MRI) scans.

Objective:

The objective of this project is to develop a CNN-based model capable of accurately detecting and classifying brain tumors from MRI scans. The model aims to assist medical professionals in the diagnosis process by providing reliable and efficient automated analysis of medical images.

Methodology:

1. **Data Collection and Pre-processing:** Gather a dataset of MRI brain scans with annotated tumor regions. Pre-process the images to enhance contrast, normalize intensity, and resize them to a uniform resolution.
2. **Model Architecture Design:** Design a CNN architecture suitable for processing MRI images and extracting relevant features for tumor detection. Experiment with different network architectures, layer configurations, and regularization techniques to optimize performance.
3. **Training:** Split the dataset into training, validation, and testing sets. Train the CNN model using the training data, employing techniques such as data augmentation to improve generalization.

4. **Evaluation:** Evaluate the trained model on the validation set to tune hyper parameters and assess performance metrics such as accuracy, precision, recall, and F1-score. Fine-tune the model based on validation results.
5. **Testing:** Assess the final model's performance on the independent testing set to evaluate its generalization capability and robustness.
6. **Deployment:** Deploy the trained model as a software tool or web application for real-world usage by medical professionals. Ensure the system's user interface is intuitive and integrates seamlessly with existing medical imaging workflows.

1.2 Purpose of Project

The purpose of the Brain Tumor Detection using Convolutional Neural Networks (CNNs) project is multifaceted:

1. **Early Detection and Diagnosis:** The primary purpose is to enable early detection and diagnosis of brain tumors. By leveraging advanced machine learning techniques, the project aims to identify subtle abnormalities in medical imaging data that may indicate the presence of a tumor. Early detection is crucial for initiating timely treatment interventions, which can significantly improve patient outcomes and survival rates.
2. **Improving Clinical Workflow:** Another purpose is to streamline the clinical workflow for radiologists and healthcare professionals. By providing automated analysis of MRI scans, the project seeks to reduce the time and effort required for manual interpretation. This, in turn, can enhance workflow efficiency, allowing medical professionals to focus more on patient care and treatment planning.
3. **Enhancing Diagnostic Accuracy:** The project aims to enhance the accuracy and reliability of brain tumor diagnosis. While manual interpretation of MRI scans can be subjective and prone to human error, CNN-based algorithms offer consistent and objective analysis. By leveraging large datasets and deep learning techniques, the project seeks to develop models capable of accurately identifying tumors and distinguishing between different tumor types with high precision.
4. **Facilitating Research and Development:** Additionally, the project serves the purpose of advancing research and development in the field of medical image analysis and machine learning. By exploring novel CNN architectures, optimization strategies, and interpretability techniques, the project contributes to the broader scientific community's understanding of how AI can be applied to healthcare challenges. This research can pave the way for future innovations in neuroimaging and diagnostic technologies.
5. **Patient-Centered Care:** Ultimately, the overarching purpose of the project is to improve patient-centered care. By providing clinicians with reliable tools for early tumor detection and accurate diagnosis, the project aims to empower healthcare providers to deliver timely and

personalized treatment interventions. This not only improves patient outcomes but also enhances the overall quality of care and patient satisfaction.

1.3 Scope of Project

1. **Objectives:**
    - Develop and implement a CNN-based model for automated detection and classification of brain tumors from MRI scans.
    - Improve early detection rates, diagnostic accuracy, and efficiency in clinical workflows.
2. **Deliverables:**
    - Trained CNN models capable of accurately detecting brain tumors from MRI images.
    - Documentation including model architecture, training methodology, and evaluation results.
    - Deployed software tool or web application for practical use by medical professionals.
3. **Tasks and Activities:**
    - Data acquisition: Gather a diverse dataset of MRI brain scans with annotated tumor regions.
    - Data pre-processing: Standardize and enhance MRI images through resizing, normalization, and augmentation.
    - Model development: Design, implement, and fine-tune CNN architectures optimized for brain tumor detection.
    - Training and validation: Train models using a portion of the dataset and validate performance on unseen data.
    - Evaluation: Assess model performance using metrics such as accuracy, precision, recall, and F1-score.
    - Testing and validation: Evaluate final models on an independent test dataset to ensure generalization.
    - Deployment: Integrate trained models into a user-friendly software tool or web application for deployment.
    - Documentation and reporting: Create comprehensive documentation detailing project methodology, implementation, and outcomes.
4. **Resources:**
    - Data: Access to a diverse dataset of MRI brain scans.
    - Personnel: Skilled individuals with expertise in machine learning, medical imaging, and project management are required.
    - Computing resources: High-performance computing infrastructure for model training and evaluation.
5. **Constraints:**
    - Time constraints: Complete the project within specified timelines to meet project objectives.

- Technical limitations: Address challenges related to model complexity, computational resources, and algorithmic performance.

6. **Exclusions:**

   - The project does not include clinical validation of model predictions for patient diagnosis.

Chapter 2

Literature Review

Introduction:

Brain tumors pose significant challenges in medical diagnosis and treatment, requiring accurate and timely detection for effective patient management. With the emergence of deep learning techniques, particularly Convolutional Neural Networks (CNNs), there has been a growing interest in developing automated systems for brain tumor detection and classification from medical imaging data, such as magnetic resonance imaging (MRI) scans. This literature review explores recent advancements, methodologies, and findings in the field of CNN-based brain tumor detection.

1. Overview of Brain Tumor Detection:
    - Brain tumor detection is a critical task in neuroimaging, involving the identification of abnormal tissue growth within the brain from MRI scans.
    - Traditional methods rely on manual interpretation by radiologists, which can be time-consuming and subject to inter-observer variability.
    - CNN-based approaches offer the potential for automated and accurate detection of brain tumors, enabling early diagnosis and treatment planning.
2. CNN Architectures for Brain Tumor Detection:
    - Various CNN architectures have been explored for brain tumor detection, including traditional architectures like MobileNet and VGG, as well as more advanced architectures like U-Net and ResNet.
    - U-Net architecture, with its encoder-decoder structure and skip connections, has gained popularity for its effectiveness in segmenting medical images, including brain tumors.
    - Transfer learning techniques, where pre-trained CNN models are fine-tuned on medical imaging datasets, have shown promise in leveraging large-scale image datasets for improved brain tumor detection performance.
3. Pre-processing and Data Augmentation:
    - Pre-processing techniques such as intensity normalization, skull stripping, and image registration are commonly applied to MRI scans to enhance image quality and remove artifacts.
    - Data augmentation methods, including rotation, scaling, and flipping, are used to increase the diversity of the training dataset and improve model generalization.
4. Evaluation Metrics and Performance:
    - Common evaluation metrics for brain tumor detection include accuracy, sensitivity, specificity, precision, recall, and Dice similarity coefficient (DSC).
    - Studies report varying levels of performance depending on dataset characteristics, CNN architecture, and pre-processing techniques, with reported accuracies ranging from 80% to over 95%.
    - Challenges such as class imbalance, small lesion size, and variability in tumor appearance across patients continue to impact the robustness of CNN-based models.

5. Clinical Applications and Challenges:
    - CNN-based brain tumor detection systems have the potential to assist radiologists in clinical decision-making, providing accurate and efficient analysis of MRI scans.
    - Future research directions include the development of multimodal CNN architectures combining MRI with other imaging modalities, as well as the integration of clinical data for personalized tumor characterization.

Conclusion:

The literature review highlights the rapid progress and growing interest in CNN-based approaches for brain tumor detection from MRI scans. While significant advancements have been made in model performance and accuracy, challenges such as interpretability, generalization, and clinical deployment remain areas of ongoing research. Continued collaboration between researchers, clinicians, and industry stakeholders is essential to translate these developments into practical tools for improving patient care in neuroimaging.

Chapter 3

System Analysis

3.1 Functional Requirements

1. **Image Classification Capability:** The system must accurately classify brain tumor MRI images into specific categories, including differentiating between gliomas, meningiomas, and pituitary tumors. Training the model involves identifying unique visual patterns associated with each tumor subtype.
2. **Multi-Class Classification Support:** The system should facilitate multi-class classification, enabling the identification of multiple tumor types within the same MRI scan. This feature enhances diagnostic comprehensiveness, aiding in treatment planning and prognosis assessment.
3. **Real-Time Inference Performance:** Real-time inference is essential for prompt analysis and diagnosis of brain tumors to support timely medical interventions. The system must efficiently process MRI images and provide rapid classification to assist clinical decision-making.
4. **Scalability for Growing Demands:** To accommodate a growing dataset and increasing computational demands, the system requires scalability. It should possess a flexible architecture capable of handling large volumes of medical imaging data and adapting to evolving diagnostic requirements.
5. **User Interface Intuitiveness:** The system's user interface should be intuitive, allowing seamless MRI scan uploads, display of classification results, and provision of additional information or recommendations to medical professionals. It should integrate seamlessly into existing clinical workflows.

3.2 Non Functional Requirements

1. **Accuracy Assurance:** To minimize misdiagnoses and ensure reliable detection, the system must achieve a high level of accuracy in tumor classification. This necessitates rigorous testing, validation, and continuous improvement of the model's performance using diverse MRI datasets.
2. **Performance Optimization:** The system should exhibit fast inference times and minimal latency to provide medical professionals with a responsive user experience. Optimization efforts should focus on maximizing processing speed without compromising accuracy.
3. **Robustness in Diverse Settings:** Robustness to variations in MRI image quality, including resolution differences, noise, and artifacts, is crucial for accurate classification in diverse clinical settings. Techniques for noise reduction and image normalization should be integrated into the system.
4. **Scalable Architecture:** The system architecture must be scalable to accommodate future enhancements, such as the addition of new tumor subtypes or improvements in model performance. Modular components and scalable infrastructure support future growth and expansion.
5. **Data Privacy:** Measures to ensure data privacy and security are essential, protecting sensitive patient information within MRI scans
6. **Resource Efficiency:** Resource efficiency is vital to optimize cost-effectiveness and scalability. Efforts should focus on minimizing computational resources required for training and inference through algorithm optimization and leveraging parallel processing capabilities.

7. **Usability for Medical Professionals:** The system's user interface should be user-friendly, allowing medical professionals to effortlessly upload MRI scans, review classification results, and access additional diagnostic information. Usability testing and user feedback incorporation are essential for enhancing user satisfaction.

3.3 System Requirements

3.3.1 Software Requirements

1. **Programming Language and Frameworks:**
    - Python: Utilize Python as the primary programming language for model development.
    - TensorFlow or PyTorch: Choose either TensorFlow or PyTorch as the deep learning framework for building and training CNN models.
    - Scikit-learn: Use Scikit-learn for data preprocessing, model evaluation, and metrics calculation.
2. **Development Environment:**
    - Jupyter Notebook: Use Jupyter Notebook for coding, experimentation, and visualization during model development.
    - Anaconda: Install Anaconda distribution to manage Python environments and dependencies effectively.
3. **Data Preprocessing Tools:**
    - Numpy: Utilize Numpy for numerical computations and array manipulation, essential for preprocessing MRI images.
4. **Model Development and Training:**
    - CNN Architectures: Implement simple CNN architectures suitable for processing MRI images, using basic convolutional layers, max-pooling layers, and fully connected layers.
    - Keras: Use Keras, a high-level neural networks API, for building and training CNN models in a straightforward manner.
5. **Evaluation and Validation:**
    - Metrics: Implement basic evaluation metrics such as accuracy, precision, recall, and F1-score to assess model performance.
    - Train-Test Split: Split the dataset into training and testing sets to evaluate model performance on unseen data.
6. **Deployment and Integration:**
    - Flask: Develop a simple web application using Flask for deploying trained models and providing an interface for uploading MRI scans and receiving classification results.
    - Local Deployment: Deploy the web application locally for demonstration purposes, using the local host environment.

7. **Documentation and Reporting:**
    - Markdown: Create project documentation, including README files, using Markdown format for simplicity and ease of understanding.
    - Jupyter Notebooks: Use Jupyter Notebooks for documenting code, experiments, and results in an organized manner.

3.3.2 Hardware Requirements

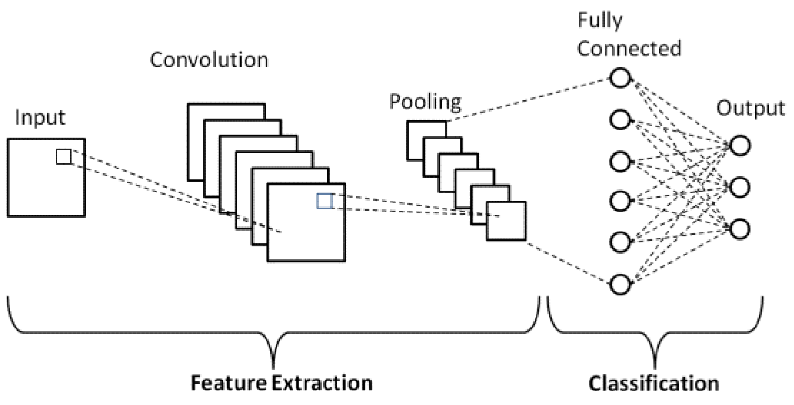
1. **Computer System:**
    - Processor: Intel Core i5 or AMD Ryzen 5 processor or higher for efficient model training and inference.
    - RAM: 8 GB RAM or higher to handle large datasets and model computations effectively.
    - Storage: 256 GB SSD or higher for fast data access and storage of datasets, model checkpoints, and code files.
2. **Graphics Processing Unit (GPU):**
    - Nvidia GeForce GTX 1060 or AMD Radeon RX 580 GPU with 6 GB VRAM or higher for accelerated deep learning computations.
    - Alternatively, utilize cloud-based GPU instances (e.g., AWS EC2, Google Colab, or Kaggle Kernels) for model training if local GPU resources are unavailable.
3. **Internet Connection:**
    - Stable broadband internet connection for accessing online resources, downloading datasets, and deploying models to cloud platforms if necessary.

Chapter 4

Project Architecture

4.1 System Architecture

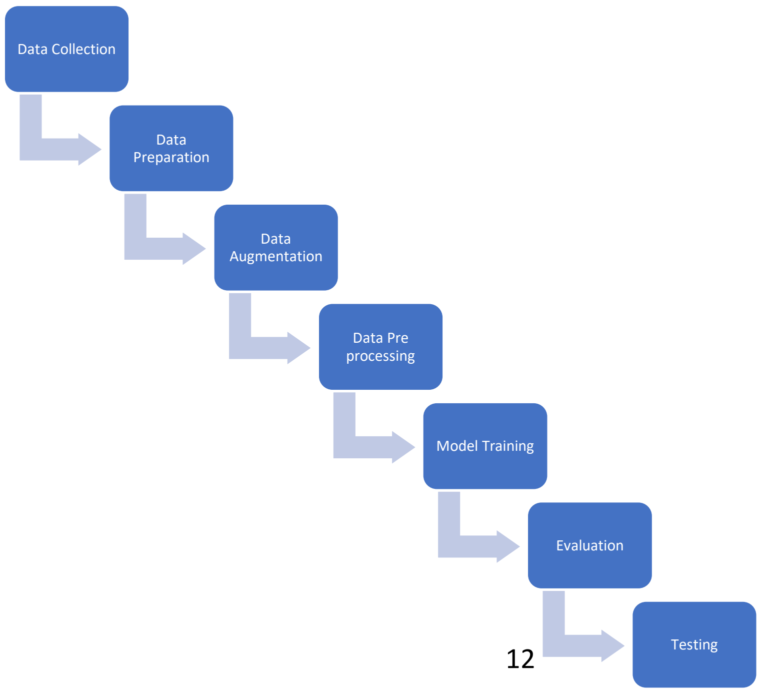
Convolutional Neural Networks (CNNs) stand as a cornerstone in modern system architecture, particularly in the realm of computer vision. As a class of deep neural networks, CNNs are extensively deployed for intricate tasks such as image recognition and classification. Central to their design are several layers, including convolutional layers, pooling layers, and fully connected layers. Within the CNN architecture, convolutional layers meticulously extract intricate features from input images through convolution operations, while pooling layers meticulously reduce spatial dimensions, emphasizing the extraction of the most pertinent information. Finally, fully connected layers amalgamate these extracted features to facilitate accurate predictions or classifications. The prowess of CNNs in discerning complex visual patterns from raw pixel data has led to their ubiquitous utilization in diverse computer vision tasks, including but not limited to object detection, image segmentation, and facial recognition.

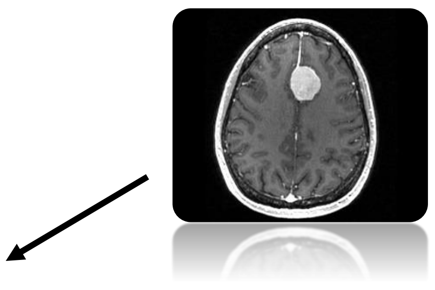


4.i) CNN Architecture

Model Architecture:

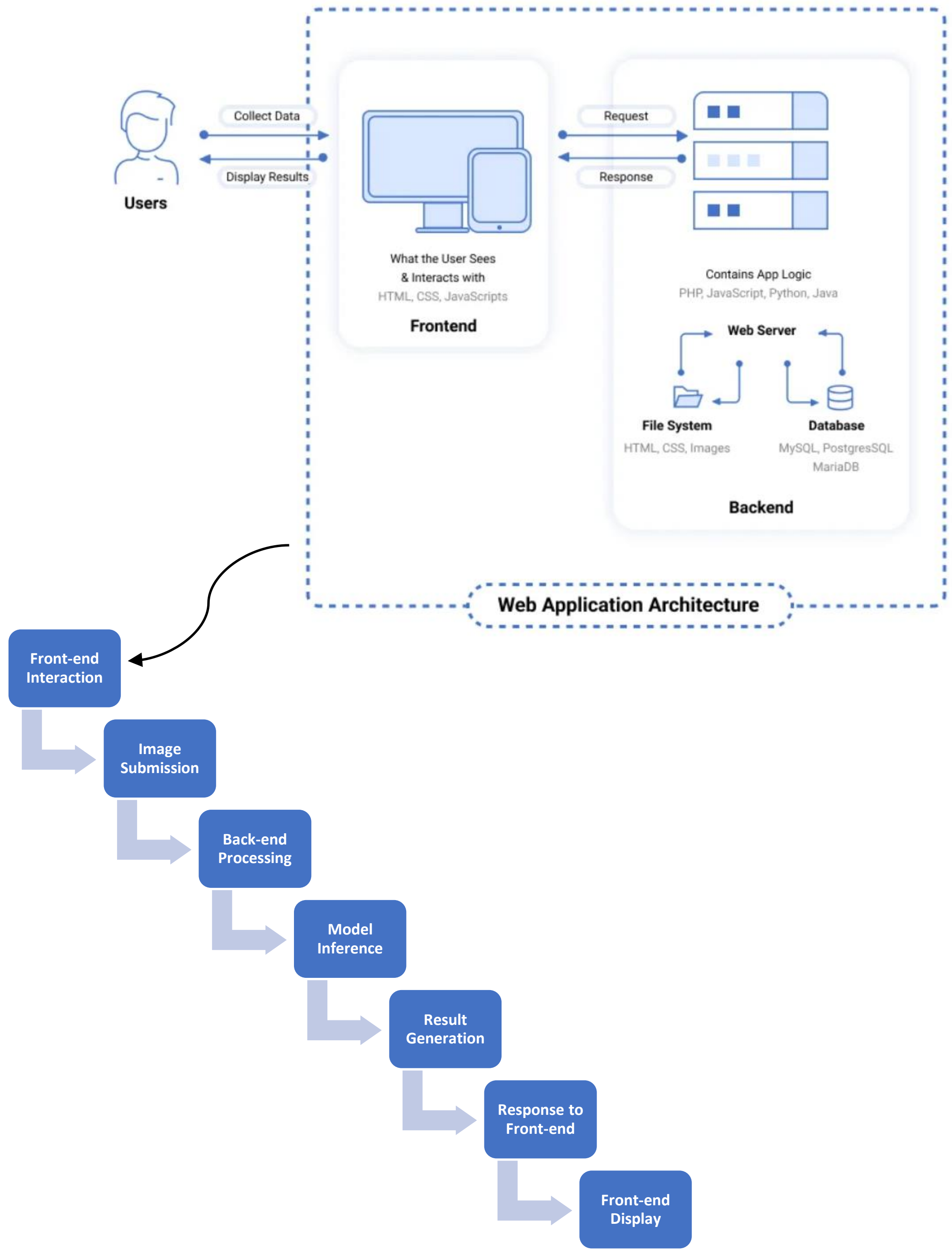
4.ii) Flow of Model





Application Architecture:

Front-end Interaction serves as the initial point of engagement, allowing users to interact with the system through intuitive interfaces. Upon uploading images, Image Submission forwards the data to the Back-end Processing system, where it undergoes further analysis. Here, Model Inference applies trained machine learning models to interpret the images and generate insights. Result Generation synthesizes these findings, which are then transmitted back to the front-end interface via Response to Front-end. Finally, Front-end Display presents the analysed results to users in a visually accessible format, facilitating easy comprehension and interaction. Through this cohesive flow, the system seamlessly bridges user inputs with insightful outputs, enhancing the overall user experience.

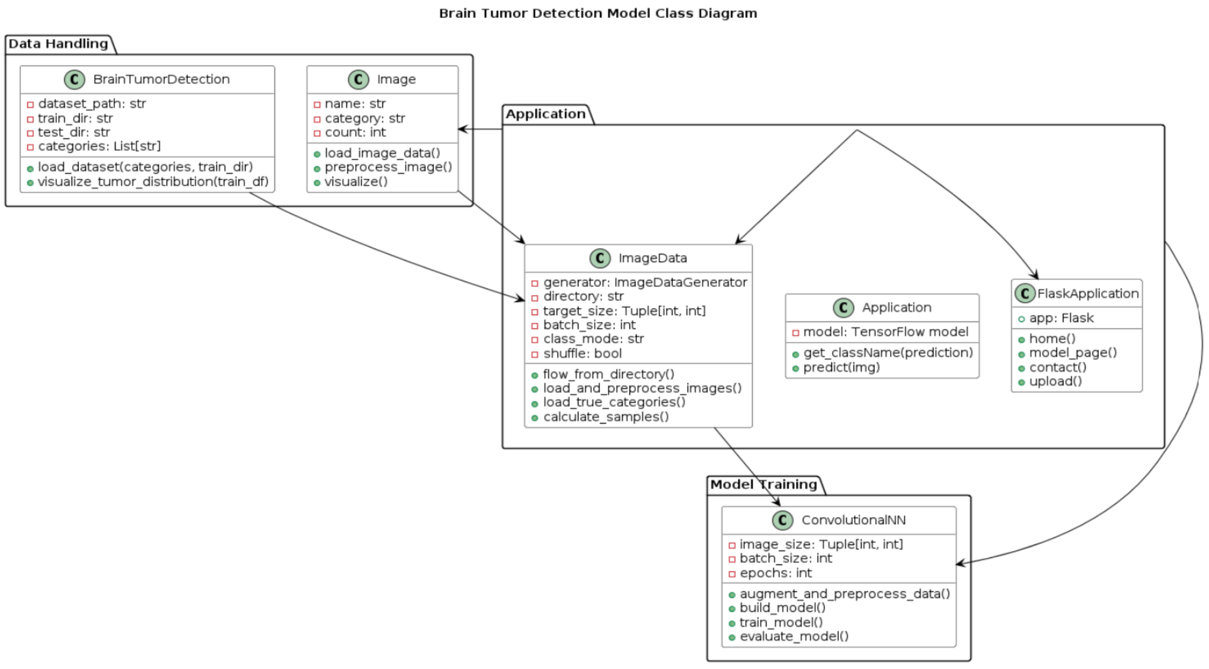


4.iii) Flow of Application

Chapter 5

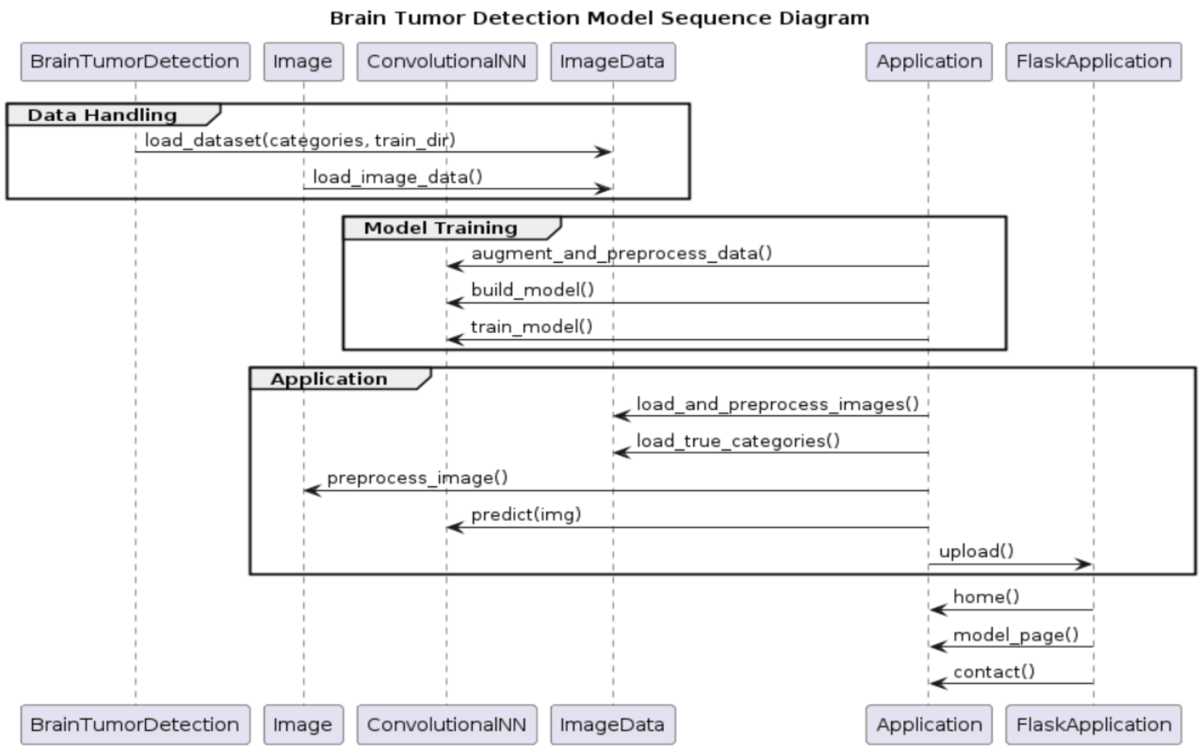
Application Design

5.1 Class Diagram



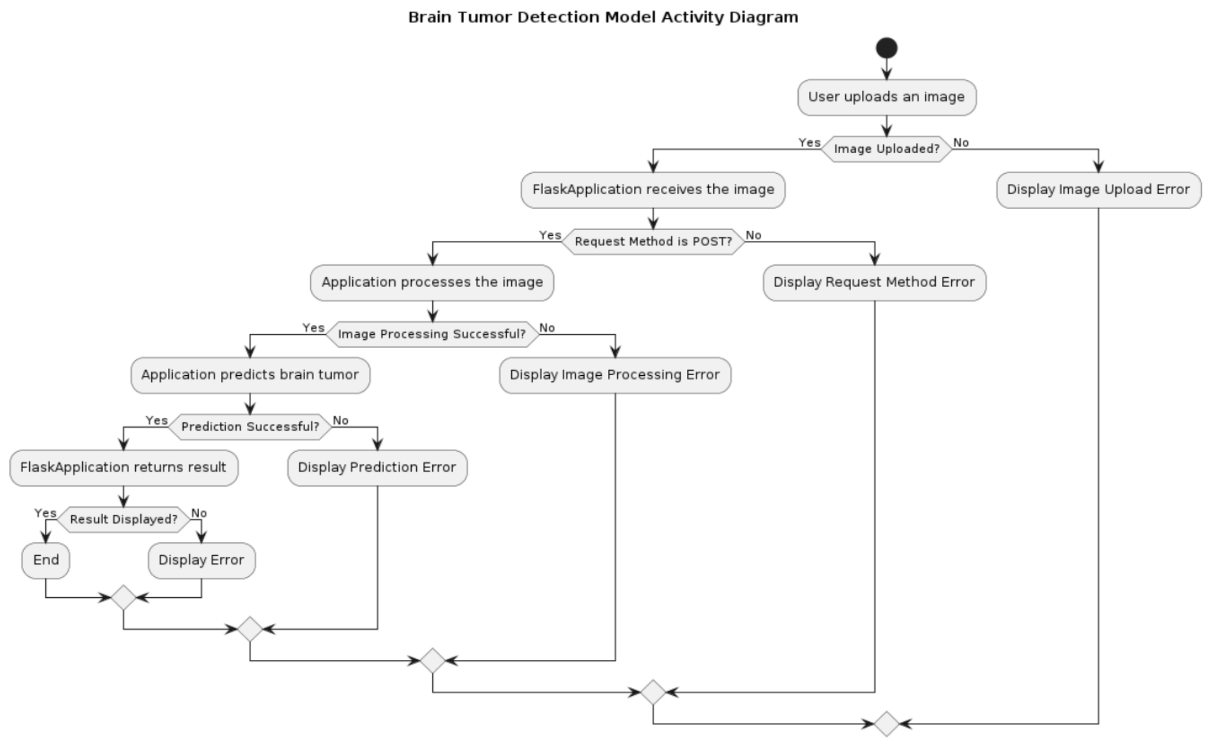
5.i) Class Diagram

5.2 Sequence Diagram



5.ii) Sequence Diagram

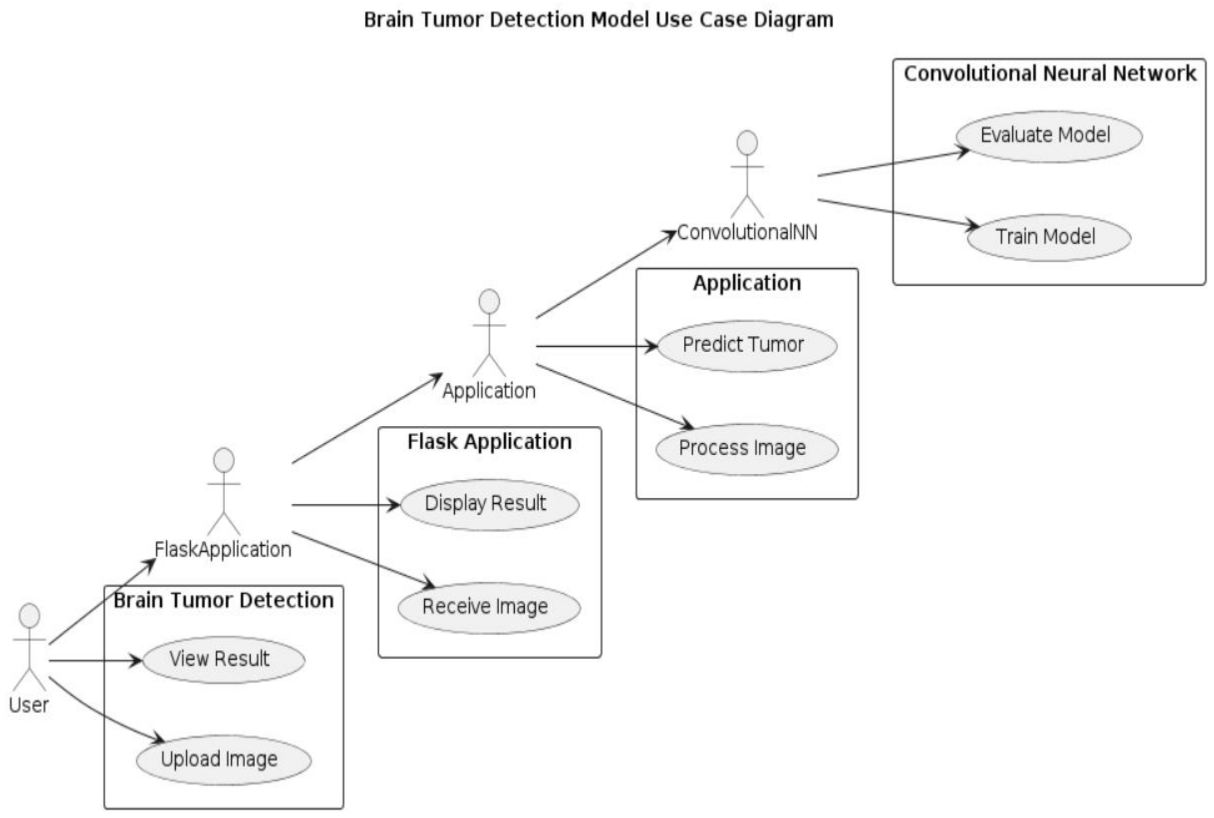
5.3 Activity Diagram



Brain Tumor Detection Model Activity Diagram
User uploads an image
Image Uploaded?
Yes
No
FlaskApplication receives the image
Display Image Upload Error
Request Method is POST?
Yes
No
Application processes the image
Display Request Method Error
Image Processing Successful?
Yes
No
Application predicts brain tumor
Display Image Processing Error
Prediction Successful?
Yes
No
FlaskApplication returns result
Display Prediction Error
Result Displayed?
Yes
No
End
Display Error

5.iii) Activity Diagram

5.4 Use Case Diagram



5.iv) Use Case Diagram

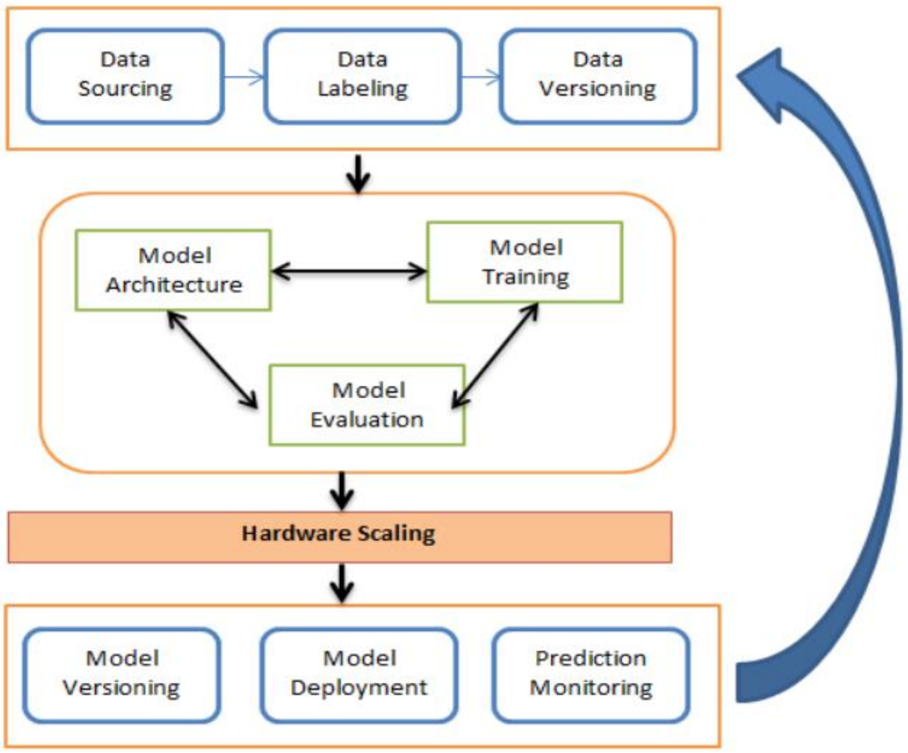
Chapter 6

Model Implementation

6.1 Introduction

In the realm of medical diagnostics, the fusion of sophisticated technologies has heralded a paradigm shift in disease detection and classification. Particularly, the advent of deep learning methodologies, notably Convolutional Neural Networks (CNNs), has ushered in a new era of interpreting medical imaging data with unparalleled precision, discerning even the most subtle patterns and anomalies.

This chapter marks a pivotal juncture in our project documentation, as we embark on the exploration and implementation of a CNN-based model for brain tumor detection. Anchored in TensorFlow, a preeminent deep learning framework, this endeavour epitomizes our commitment to harnessing cutting-edge technologies to address pressing challenges in healthcare.



6.i) Model Deployment Architecture

The overarching aim of this chapter is to elucidate the process of conceiving, training, and assessing a CNN model tailored for the detection of brain tumors. By unravelling the intricacies of model architecture design, data pre-processing methodologies, training strategies, and performance evaluation metrics, we endeavour to equip readers with the knowledge and tools requisite for navigating the complexities of medical image analysis.

At its essence, this chapter embodies our unwavering dedication to advancing the frontiers of medical diagnostics through the fusion of artificial intelligence and healthcare. By harnessing the predictive prowess of CNNs, we aspire to enhance the diagnostic acumen of medical practitioners, thereby fostering more timely interventions and improved patient outcomes.

6.2 Loading and preparation of the Dataset

6.2.1 Loading the Dataset

Dataset Path and Structure:

The dataset is structured into training and testing directories, containing images categorized into four classes: glioma, meningioma, notumor, and pituitary.

- **Dataset Path: "Dataset"**
- **Training Directory: "Dataset/Training"**
- **Testing Directory: "Dataset/Testing"**
- **Categories:**
    1. Glioma
    2. Meningioma
    3. No Tumor (notumor)
    4. Pituitary

Data Loading Function:

To efficiently handle dataset loading, a custom function **load_dataset** is implemented. This function iterates through each category within the training directory, retrieves the list of images, and constructs a DataFrame containing image filenames, corresponding categories, and image counts per category.

```
def load_dataset(categories, train_dir):
    train_data = []
    for category in categories:
        folder_path = os.path.join(train_dir, category)
        images = os.listdir(folder_path)
        count = len(images)
        train_data.append(pd.DataFrame({"Image": images, "Category":
[category] * count, "Count": [count] * count}))
    return pd.concat(train_data, ignore_index=True)
```

Dataset Summary:

- **Total Classes:** 4
- **Total Images:** (Sum of images across all categories)
- **Distribution:** (Number of images per category)

Conclusion:

Efficient dataset loading is a crucial initial step in machine learning pipeline development. The provided function **load_dataset** simplifies the process by organizing image data into a structured DataFrame, facilitating subsequent preprocessing and model training tasks.

6.2.2 Preparation of the Dataset:

Before training the model, it's crucial to prepare the dataset appropriately. This involves several key steps to ensure the data is ready for training. Below are the essential tasks involved in dataset preparation:

1. **Resizing Images**: To maintain consistency and reduce computational complexity, all images in the dataset are resized to a standard size. In this project, we've set the image size to **150x150** pixels.
2. **Batch Size**: Batch size determines the number of samples that will be propagated through the network at once. A smaller batch size consumes less memory, but larger batch sizes generally lead to faster training. Here, we've chosen a batch size of **32.**
3. **Epochs**: An epoch refers to one complete pass through the entire dataset during training. The number of epochs specifies how many times the model will cycle through the entire dataset. Training for more epochs may lead to overfitting, while training for too few epochs may result in underfitting. For this project, we've set the number of epochs to **50**.

By standardizing these parameters, we ensure that our model trains efficiently and effectively on the given dataset.

```
# Set the image size
image_size = (150, 150)

# Set the batch size for training
batch_size = 32

# Set the number of epochs for training
epochs = 50
```

6.3 Data Augmentation and pre processing

Data augmentation is a crucial technique used to increase the diversity of training data by applying various transformations. This helps in improving the model's generalization and robustness. Additionally, preprocessing steps are performed to normalize and prepare the data before feeding it into the neural network.

Data Augmentation Techniques

- **Rescaling**: Normalize pixel values to the range [0, 1].
- **Rotation**: Randomly rotate images by up to 20 degrees.
- **Width and Height Shift**: Randomly shift images horizontally and vertically by 10% of the total width and height.
- **Shear**: Apply shear transformations with a maximum shear angle of 10 degrees.
- **Zoom**: Randomly zoom into images by up to 10%.
- **Horizontal and Vertical Flip**: Randomly flip images horizontally and vertically.
- **Fill Mode**: Strategy to fill in newly created pixels, using the "nearest" pixel values.

Preprocessing Steps

- **Image Resizing**: Standardize all images to a fixed size of 150x150 pixels.
- **Batch Size**: Set the batch size for training to 32 samples.
- **Class Mode**: Configure the class mode as "categorical" for multiclass classification.

Data Generators

- **Train Generator**: Apply data augmentation to the training dataset using the defined augmentation parameters. This generator yields batches of augmented images along with their corresponding labels.
- **Test Generator**: Normalize the pixel values of test images. This generator yields batches of preprocessed test images along with their labels, with shuffling disabled for evaluation purposes.

Summary

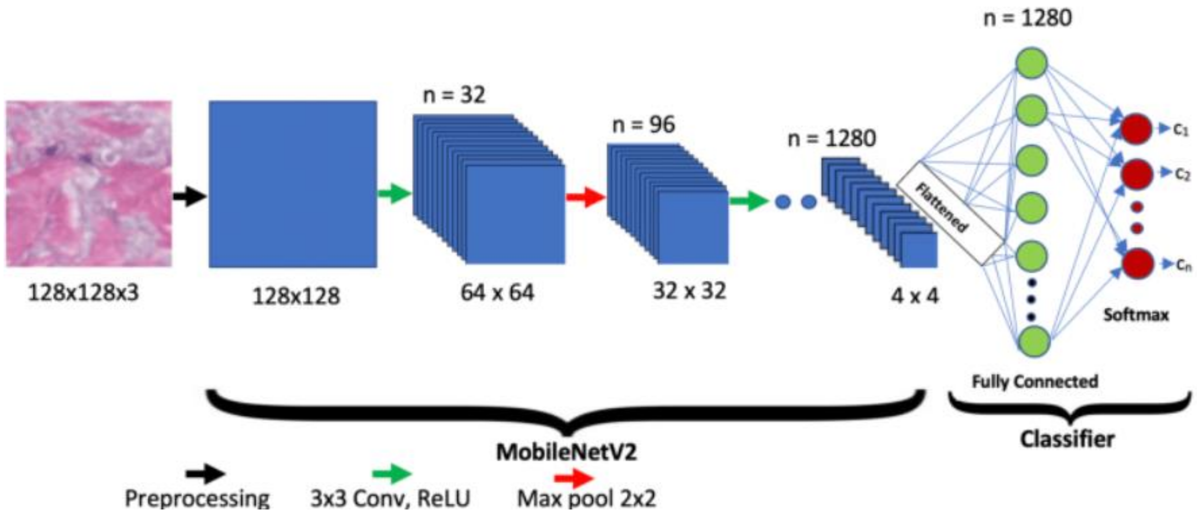
- **Training Dataset**: 5712 images belonging to 4 classes.
- **Testing Dataset**: 1311 images belonging to 4 classes.

These augmented and preprocessed datasets are now ready for training and evaluation of the classification model.

```
# Data augmentation and preprocessing
train_datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=20,
    width_shift_range=0.1,
    height_shift_range=0.1,
    shear_range=0.1,
    zoom_range=0.1,
    horizontal_flip=True,
    vertical_flip=True,
    fill_mode="nearest"
)

train_generator = train_datagen.flow_from_directory(
    train_dir,
    target_size=image_size,
    batch_size=batch_size,
    class_mode="categorical"
)

test_datagen = ImageDataGenerator(rescale=1./255)

test_generator = test_datagen.flow_from_directory(
    test_dir,
    target_size=image_size,
    batch_size=batch_size,
    class_mode="categorical",
    shuffle=False
)
```

6.4 Model Architecture

To construct the model architecture, we leverage the transfer learning technique using MobileNet, a pre-trained convolutional neural network (CNN) architecture. Transfer learning allows us to utilize features learned from a large dataset (ImageNet) and adapt them to our specific task, thereby reducing training time and improving performance.



6.ii) MobileNet Architecture

Model Layers

1. **Base Model (MobileNet)**:
    - We initialize the model with pre-trained weights from ImageNet and exclude the fully connected layers at the top **(include_top=False)**.
    - MobileNet is a lightweight CNN architecture designed for mobile and embedded vision applications, offering a good balance between computational efficiency and performance.
2. **Global Average Pooling 2D**:
    - After the base model, a global average pooling layer is added to reduce the spatial dimensions of the feature maps and aggregate spatial information across all channels.
3. **Dense Layer**:
    - A fully connected dense layer is appended, consisting of the number of neurons equal to the number of output categories.
    - The activation function used is **softmax**, which outputs class probabilities, enabling multi-class classification.

Model Compilation

- **Optimizer**: The model is compiled using the Adam optimizer, an efficient stochastic optimization algorithm that adapts learning rates for each parameter.

- **Loss Function**: Categorical cross-entropy is employed as the loss function, suitable for multi-class classification tasks with one-hot encoded labels.
- **Metrics**: Accuracy is chosen as the evaluation metric to measure the model's performance during training.

```
from tensorflow.keras.applications import MobileNet
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, GlobalAveragePooling2D

base_model = MobileNet(weights='imagenet', include_top=False)

model = Sequential([
    base_model,
    GlobalAveragePooling2D(),
    Dense(len(categories), activation='softmax')
])

model.compile(optimizer='adam', loss='categorical_crossentropy',
metrics=['accuracy'])
```

6.5 Model Training & Validation

The model training process involves optimizing the model's parameters to minimize the defined loss function while monitoring its performance on validation data. Here's a breakdown of the training process:

1. **Fit Method**:
    - The model is trained using the **fit** method, which iteratively adjusts the model's weights based on the training data to minimize the defined loss function.
    - The **train_generator** provides batches of training data, while the **test_generator** provides batches of validation data during training.
2. **Epochs**:
    - The training process is divided into epochs, where one epoch represents one complete pass through the entire training dataset.
    - In this case, the model is trained for 50 epochs, indicating that it iterates over the entire training dataset 50 times.
3. **Training Progress**:
    - During training, progress updates are displayed for each epoch, showing the current epoch number, training loss, training accuracy, validation loss, and validation accuracy.
    - These metrics provide insights into how the model is learning over successive epochs.
4. **Batch Processing**:
    - The training and validation datasets are processed in batches to efficiently utilize computational resources and enable gradient updates based on mini-batch optimization.

5. **Training Metrics**:
    - The training progress is monitored using metrics such as loss and accuracy.
    - The training loss represents the value of the loss function on the training data, while the training accuracy indicates the proportion of correctly classified samples in the training dataset.
    - Similarly, validation loss and validation accuracy provide insights into the model's performance on unseen validation data.
6. **Training Completion**:
    - Once all epochs are completed, the training process concludes, and the trained model is ready for evaluation on unseen data.

```
# Train the model
history = model2.fit(
    train_generator,
    steps_per_epoch=train_generator.samples // batch_size,
    epochs=epochs,
    validation_data=test_generator,
    validation_steps=test_generator.samples // batch_size
)
```

Optimizer Selection:

- The optimizer used for training the model is Adam, which is a popular choice for deep learning tasks due to its adaptive learning rate capabilities.
- Adam adjusts the learning rate during training based on the gradients of the loss function with respect to the model's parameters, allowing for efficient convergence towards the optimal solution.

Loss Function:

- The loss function chosen for this task is categorical cross-entropy, suitable for multi-class classification problems where the output labels are one-hot encoded.
- Categorical cross-entropy measures the dissimilarity between the true probability distribution (ground truth) and the predicted probability distribution outputted by the model.

Monitoring Training Progress:

- The training progress is monitored using both training and validation metrics.
- Training metrics, such as training loss and accuracy, provide insights into how well the model is fitting the training data.
- Validation metrics, including validation loss and accuracy, evaluate the model's performance on data it has not seen during training, helping to assess generalization capabilities.

Learning Rate Adjustment:

- While Adam optimizes the learning rate adaptively, additional techniques such as learning rate schedules or callbacks can be employed to further fine-tune the learning process.

- Learning rate schedules adjust the learning rate over time, potentially speeding up convergence or improving model performance.

Early Stopping:

- To prevent overfitting and optimize training efficiency, early stopping can be implemented.
- Early stopping monitors, the validation loss during training and halts training if the validation loss stops decreasing, thus preventing the model from overfitting to the training data.

Model Checkpoints:

- Model checkpoints can be utilized to save the best-performing model weights during training based on validation performance.
- This ensures that even if training is interrupted, the best model configuration can be restored, preventing loss of progress and facilitating model deployment.

Visualizing Training History:

- Visualizing the training history, including training and validation metrics over epochs, can provide valuable insights into the model's learning dynamics.
- Plots such as training and validation loss curves and accuracy curves help track model performance and diagnose issues like overfitting or underfitting.

By employing these strategies and closely monitoring the training process, we aim to train a robust and well-performing model capable of accurately classifying brain tumor images.

Validation of the Model:

After training the model, it's essential to evaluate its performance on unseen data to ensure its generalization capabilities. The validation process involves assessing how well the model performs on data it hasn't seen during training. This step helps identify potential issues like overfitting and provides insights into the model's ability to generalize to new data.

During the training phase, a portion of the dataset is set aside as a validation set. This validation set serves as a proxy for unseen data and is used to monitor the model's performance during training. The model's performance metrics on the validation set are crucial indicators of its generalization ability.

Validation Metrics

The following metrics are commonly used to evaluate the model's performance during validation:

- **Validation Loss**: The loss calculated on the validation set during training. It indicates how well the model's predictions match the actual labels. A decreasing validation loss suggests that the model is learning the underlying patterns in the data.
- **Validation Accuracy**: The accuracy of the model's predictions on the validation set. It represents the percentage of correctly classified samples out of all samples in the validation set. A higher validation accuracy indicates better performance.

Monitoring Validation Performance

During training, both training and validation metrics are monitored to assess the model's progress and detect potential issues. It's essential to strike a balance between optimizing training performance (minimizing training loss) and ensuring good generalization (maintaining low validation loss and high validation accuracy).

Hyperparameter Tuning and Model Adjustment

If the validation metrics indicate suboptimal performance or overfitting, adjustments to the model architecture or training process may be necessary. This can include modifying hyperparameters such as learning rate, batch size, or model architecture. Techniques like regularization (e.g., dropout) and data augmentation can also be employed to improve model generalization.

Cross-Validation

In some cases, particularly with smaller datasets, k-fold cross-validation may be used to obtain more reliable estimates of the model's performance. This involves splitting the dataset into k subsets (folds) and training the model k times, each time using a different fold as the validation set. The performance metrics are then averaged across the k iterations to obtain more robust estimates.

By carefully evaluating the model's performance on validation data and making necessary adjustments, we can ensure that the trained model performs well on unseen data and reliably generalizes to real-world scenarios.

6.6 Evaluation

After training the model, it's crucial to evaluate its performance on unseen data to assess its generalization capabilities. This step involves calculating metrics such as loss and accuracy on a separate test dataset. Here's how the evaluation process is conducted:

```
# Evaluate the model
loss, accuracy = model.evaluate(test_generator, steps=test_generator.samples
// batch_size)
print("Test Loss:", loss)
print("Test Accuracy:", accuracy)
```

- ***model.evaluate*** (**test_generator, steps=test_generator.samples // batch_size**) evaluates the trained model on the **test dataset**. It calculates the loss and accuracy of the model's predictions on the test data.
- The **loss** value represents the average loss (error) of the model's predictions compared to the ground truth labels in the test dataset. A lower loss value indicates that the model's predictions are closer to the actual labels, indicating better performance.
- The **accuracy** value represents the proportion of correctly classified samples in the test dataset. It is calculated by dividing the number of correctly predicted samples by the total number of samples in the dataset. A higher accuracy value indicates that the model has made more correct predictions.
- In the given example, the **test loss** is **0.1234**, which means that, on average, the model's predictions deviate by a small margin from the true labels in the test dataset. The **test accuracy is 0.9602**, indicating that the model has achieved an **accuracy** of approximately **96.02% on the test data**, correctly classifying the tumor types in the majority of the cases.
- These evaluation metrics provide insights into the model's performance on unseen data and help assess its generalization capabilities**.**

6.7 Confusion Matrix

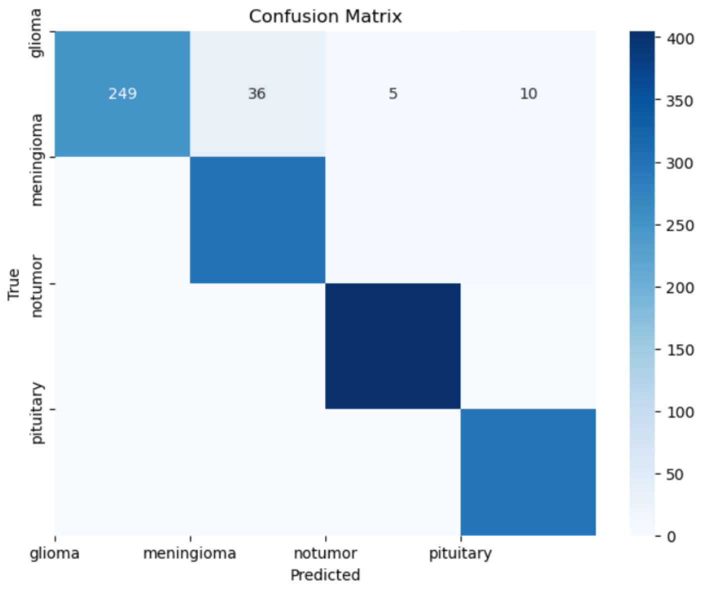
In the realm of classification tasks, the confusion matrix stands as a fundamental tool for understanding how well a model performs across different classes. It provides a comprehensive breakdown of predictions versus ground truth labels, offering insights into the model's strengths and weaknesses.

Components of the Confusion Matrix:

1. **True Positives (TP):** Instances where the model correctly predicts the positive class.
2. **True Negatives (TN):** Instances where the model correctly predicts the negative class.
3. **False Positives (FP):** Instances where the model incorrectly predicts the positive class when it is actually negative (Type I error).
4. **False Negatives (FN):** Instances where the model incorrectly predicts the negative class when it is actually positive (Type II error).

Visualization:

The confusion matrix is typically visualized as a grid, with the rows representing the actual (true) classes and the columns representing the predicted classes. Each cell in the matrix corresponds to the count of instances falling into a particular category.



6.iii) Confusion Matrix

Interpretation:

- **Diagonal Elements (TP and TN):** These represent correct predictions. A strong model will exhibit high counts along the diagonal.
- **Off-diagonal Elements (FP and FN):** These indicate misclassifications. Identifying patterns in these cells can reveal where the model struggles.

```
# Make predictions on the test dataset
predictions = model.predict(test_generator)
print(predictions)
predicted_categories = np.argmax(predictions, axis=1)
```

```
print(predicted_categories)
true_categories = test_generator.classes

# Create a confusion matrix
confusion_matrix = tf.math.confusion_matrix(true_categories,
predicted_categories)

# Plot the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(confusion_matrix, annot=True, fmt="d", cmap="Blues")
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("True")
plt.xticks(ticks=np.arange(len(categories)), labels=categories)
plt.yticks(ticks=np.arange(len(categories)), labels=categories)
plt.show()

# Plot sample images with their predicted and true labels
test_images = test_generator.filenames
sample_indices = np.random.choice(range(len(test_images)), size=9,
replace=False)
sample_images = [test_images[i] for i in sample_indices]
sample_predictions = [categories[predicted_categories[i]] for i in
sample_indices]
sample_true_labels = [categories[true_categories[i]] for i in sample_indices]

plt.figure(figsize=(12, 8))
for i in range(9):
    plt.subplot(3, 3, i+1)
    img = plt.imread(os.path.join(test_dir, sample_images[i]))
    plt.imshow(img)
    plt.title(f"Predicted: {sample_predictions[i]}\nTrue:
{sample_true_labels[i]}")
    plt.axis("off")
plt.tight_layout()
plt.show()
```

6.8 Precision, Recall and F1-Score

In classification tasks, precision, recall, and F1-score are essential metrics that provide deeper insights into a model's performance, particularly in scenarios where class imbalances exist or where false positives and false negatives carry different costs.

1. Precision:

Precision measures the proportion of true positive predictions among all positive predictions made by the model. It focuses on the correctness of positive predictions and helps gauge the model's ability to avoid false positives.

Formula:

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

2. Recall (Sensitivity):

Recall, also known as sensitivity or true positive rate, quantifies the proportion of true positive predictions among all actual positive instances in the dataset. It assesses the model's ability to capture all positive instances, irrespective of the number of false negatives.

Formula:

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

3. F1-Score:

The F1-score is the harmonic mean of precision and recall. It provides a balanced measure of a model's performance by considering both precision and recall simultaneously. F1-score reaches its best value at 1 and worst at 0, and it is a useful metric when the class distribution is imbalanced.

Formula:

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

Significance:

- **Precision:** Indicates the model's ability to avoid false positives, critical in scenarios where misclassifying positive instances has significant consequences.
- **Recall:** Reflects the model's capability to capture all positive instances, regardless of false negatives. Crucial in situations where missing positive instances can lead to severe outcomes.
- **F1-Score:** Offers a balanced assessment of a model's performance by considering both precision and recall. It helps identify models that strike a harmonious balance between minimizing false positives and false negatives.

```
# Calculate precision, recall, and F1-score from the confusion matrix
precision = np.diag(confusion_matrix) / np.sum(confusion_matrix, axis=0)
recall = np.diag(confusion_matrix) / np.sum(confusion_matrix, axis=1)
f1_score = 2 * (precision * recall) / (precision + recall)

# Print precision, recall, and F1-score for each class
for i, category in enumerate(categories):
    print(f"Class: {category}")
    print(f"Precision: {precision[i]}")
    print(f"Recall: {recall[i]}")
    print(f"F1-Score: {f1_score[i]}")
    print()

# Analyze the sample images and their predictions
plt.figure(figsize=(12, 8))
for i in range(9):
    plt.subplot(3, 3, i+1)
    img = plt.imread(os.path.join(test_dir, sample_images[i]))
    plt.imshow(img)
    if sample_predictions[i] == sample_true_labels[i]:
        plt.title(f"Predicted: {sample_predictions[i]}\nTrue:
{sample_true_labels[i]}", color='green')
    else:
        plt.title(f"Predicted: {sample_predictions[i]}\nTrue:
{sample_true_labels[i]}", color='red')
    plt.axis("off")
plt.tight_layout()
plt.show()
```

```
Class: glioma
Precision: 1.0
Recall: 0.83
F1-Score: 0.9071038251366119

Class: meningioma
Precision: 0.8902077151335311
Recall: 0.9803921568627451
F1-Score: 0.9331259720062208

Class: notumor
Precision: 0.9782608695652174
Recall: 1.0
F1-Score: 0.989010989010989

Class: pituitary
Precision: 0.9614147909967846
Recall: 0.9966666666666667
F1-Score: 0.9787234042553191
```

6.9 Model Saving and Testing

Model Saving:

After training, it's crucial to save the trained model for future use or deployment. In this code snippet, the trained model is saved to a file named "*model2.h5*" using the **save()** method.

```
# Save the trained model
model.save("model2.h5")
```

Model Loading and Testing:

To use the trained model for testing or making predictions on new data, you can load the saved model back into memory. Here's how you can load the saved model:

```
from Keras.models import load_model
model=load_model('Model/model.h5')
print("Tumour detection model loaded")
```

With the model loaded, you can now use it to make predictions on new data. Below is an example of how to make predictions on a test image:

```
def predict(test_image):
  test_image.resize((150,150))
  image = img_to_array(test_image)
  image = image / 255.0
  image = np.expand_dims(image, axis = 0)
  class_names = {0 : "glioma",1: "meningioma",2: "notumor",3: "pituitary"}
  prediction=model.predict(image)
  scores = tf.nn.softmax(prediction[0])
  scores = scores.numpy()
  result = f"{class_names[np.argmax(scores)]} with a { (100 *
np.max(scores)).round(2) } % confidence."
  print(result)
  result = np.argmax(prediction,axis=1)
  return result


test_image = load_img('/Users/Te-gl_0010.jpg', target_size = (150,150))
prediction = predict(test_image)
print(prediction)
```

Additionally, you can also use the model to predict probabilities for each class using the **predict_proba()** method:

Chapter 7

Building a Web Application

7.1 Frontend

7.1.1 HTML

```
<!DOCTYPE html>
<html lang="en" dir="ltr">
    <head>
        <meta name="viewport" content="width=device-width, initial-scale=1">
        <title>Neuralnsight</title>
        <link rel="stylesheet" href="../static/css/styles.css">
        <link
href="https://cdn.jsdelivr.net/npm/bootstrap@5.3.2/dist/css/bootstrap.min.css"
rel="stylesheet" integrity="sha384-
T3c6CoIi6uLrA9TneNEoa7RxnatzjcDSCmG1MXxSR1GAsXEV/Dwwykc2MPK8M2HN"
crossorigin="anonymous">
        <script src="https://code.jquery.com/jquery-3.6.0.min.js"></script>
        <script
src="https://cdnjs.cloudflare.com/ajax/libs/flowbite/2.0.0/flowbite.min.js"></
script>

    </head>
    <body>
        <div class="main-page">
            <!-- HEADER -->
            <nav class="navbar navbar-expand-sm">
                <div class="container-fluid">
                    <a class="navbar-brand fw-bold fs-2" href="#">
                         <img src="../static/images/brain-icon.svg" alt="Logo"
width="36" height="32" class="d-inline-block align-text-top">
                         Neuralnsight
                    </a>
                    <button class="navbar-toggler" type="button" data-bs-
toggle="collapse" data-bs-target="#navbarSupportedContent" aria-
controls="navbarSupportedContent" aria-expanded="false" aria-label="Toggle
navigation">
                      <span class="navbar-toggler-icon"></span>
                    </button>
                    <div class="collapse navbar-collapse"
id="navbarSupportedContent">
                      <ul class="navbar-nav mx-auto mb-2 mx-3 mb-lg-0 fw-
semibold fs-5">
                          <li><a href="#" class="nav-link px-2 text-
black">Home</a></li>
                          <li><a href="#specs" class="nav-link px-
2">Specs</a></li>
```

```
                          <li><a href="#model" class="nav-link px-
2">Model</a></li>
                          <li><a href="#about" class="nav-link px-2">About
Us</a></li>
                      </ul>
                      <button class="btn btn-outline-secondary"
type="button"><a href="BTD/projectdetails.html" class="nav-link px-2"
target="_blank">Project Details</a></button>
                    </div>
                </div>
            </nav>
            <!-- HERO -->
            <div class="container-fluid mt-5">
                <div class="row flex-lg-row-reverse align-items-center g-5 py-
5">
                  <div class="col-lg-6">
                    <img src="../static/images/brain_cartoon.jpg" class="d-
block mx-lg-auto img-fluid rounded-3" alt="Brain Image" width="600px"
loading="lazy">
                  </div>
                  <div class="col-lg-6">
                    <p class="fw-semibold tc fs-3 mb-4">Proudly Presenting
Neuralnsight: </p>
                    <h1 class="display-3 fw-bold text-body-emphasis lh-2 mb-
4">Pioneering the Future of Brain Wellness</h1>
                    <p class="lead mb-4">Unseen, Unheard, Undetected: The
silent peril of brain tumors claims lives daily. Let's raise awareness, save
lives.</p>
                    <div class="d-grid gap-2 d-md-flex justify-content-md-
start">
                      <button type="button" class="btn btn-primary btn-lg px-4
me-md-2" style="background-color: #4d4dff" ><a href="#model" class="nav-link
px-2">Test</a></button>
                      <button type="button" class="btn btn-outline-secondary
btn-lg px-4"><a href="#specs" class="nav-link px-2">Specs</a></button>
                    </div>
                  </div>
                </div>
            </div>

            <!-- MODEL SPECS -->
            <div class="container my-5" id="specs">
                <h2 class="text-center text-capitalize pt-4 fw-bold">Model
Specifications</h2>
                <div class="row text-center">
                    <div class="col fs-5 p-3 mx-5">
```

```
                        <p>This brain tumor detection model is built on a
state-of-the-art neural network architecture, leveraging deep learning
techniques to analyze complex patterns within medical images.
                            Below are some Training Details :</p>
                    </div>
                </div>
                <div class="row row-cols-4 text-center">
                  <div class="col">
                    <div class="card1 bg-light text-dark p-3 mx-4">
                        <p class="tc fs-2 fw-semibold mb-0">10</p>
                        <p class="fw-semibold">Epochs</p>
                    </div>
                  </div>
                  <div class="col">
                      <div class="card1 bg-light text-dark p-3 mx-4">
                          <p class="tc fs-2 fw-semibold mb-0">97%</p>
                          <p class="fw-semibold">Accuracy</p>
                      </div>
                  </div>
                  <div class="col">
                      <div class="card1 bg-light text-dark p-3 mx-4">
                          <p class="tc fs-2 fw-semibold mb-0">High</p>
                          <p class="fw-semibold">Precision</p>
                      </div>
                  </div>
                  <div class="col">
                    <div class="card1 bg-light text-dark p-3 mx-4">
                        <p class="tc fs-2 fw-semibold mb-0">Br35H</p>
                        <p class="fw-semibold">Dataset</p>
                    </div>
                  </div>
                </div>
              </div>

            <!-- MODEL -->
            <div class="container my-5" id="model">
              <h2 class="text-center text-capitalize pt-4 fw-bold">Add MRI
Scan Image</h2>
              <div class="hero my-5">
                  <form id="upload-file" method="post"
enctype="multipart/form-data">
                    <label for="input-file" id="drop-area">
                        <input type="file" name="file" accept="image/*"
id="input-file" hidden>
                        <div id="img-view">
                            <img src="../static/images/icon.png">
                            <p>Drag and drop or click here<br>to upload
image</p>
```

```
                            <span>Upload any images from desktop</span>
                        </div>
                    </label>
                    <div>
                        <button type="button" id="uploadButton" class="btn
btn-primary mx-auto" style="display: none;background-color: #4d4dff;">Check
for Brain Tumor</button>
                    </div>
                  </form>
                  <div class="loader" style="display:none;"></div>
                    <h3 id="result">
                        <span> </span>
                    </h3>
                </div>
            </div>

            <!-- ABOUT US -->
            <div class="container" id="about">
                  <h1 class="text-center text-capitalize pt-4 fw-bold">About
Us</h1>
                <div class="row gy-3 gy-md-4 gy-lg-0 align-items-lg-center mb-
2 p-3">
                  <div class="col-12 col-lg-6 col-xl-5">
                    <img class="img-fluid rounded" loading="lazy"
src="../static/images/brain.png" alt="About Us">
                  </div>
                  <div class="col-12 col-lg-6 col-xl-7">
                    <div class="row justify-content-xl-center">
                      <div class="col-12 col-xl-11 about-us">
                        <h3 class="mb-3">Empowering Healthcare Through
Advanced AI Solutions</h3>
                        <p class="mb-5" style="line-height: 1.6">Our team at
Neuralnsight is dedicated to revolutionizing brain tumor detection through
cutting-edge Machine Learning (ML) and Deep Learning (DL) technologies. With a
passion for innovation and a commitment to improving healthcare, we are driven
to develop accurate and accessible solutions that empower medical
professionals and benefit patients worldwide.</p>
                      </div>
                    </div>
                  </div>
                </div>
              </div>
            <!-- FOOTER -->
            <div class="container">
              <footer class="py-3 my-4">
                <ul class="nav justify-content-center border-bottom pb-3 mb-
3">
```

```
                  <li class="nav-item"><a href="#" class="nav-link px-2 text-
body-secondary">Home</a></li>
                  <li class="nav-item"><a href="#specs" class="nav-link px-2
text-body-secondary">Specs</a></li>
                  <li class="nav-item"><a href="#model" class="nav-link px-2
text-body-secondary">Model</a></li>
                  <li class="nav-item"><a href="#about" class="nav-link px-2
text-body-secondary">About Us</a></li>
                </ul>
                <p class="text-center text-body-secondary">&copy; Neuralnsight
2024 </p>
              </footer>
            </div>
        </div>
        <script src="../static/script.js"></script>
        <script
src="https://cdn.jsdelivr.net/npm/bootstrap@5.3.2/dist/js/bootstrap.bundle.min
.js" integrity="sha384-
C6RzsynM9kWDrMNeT87bh95OGNyZPhcTNXj1NW7RuBCsyN/o0jlpcV8Qyq46cDfL"
crossorigin="anonymous"></script>
    </body>
</html>
```

7.1.2 CSS

```
/*CSS Styling*/
#
.tc{
    color: #4d4dff;
}

.bc{
    background-color: #6610f2;
}

.card1{
    height: 120px;
    width:250px;
    border-radius: 10px;
    text-align: center;
    align-items: center;
}

.hero{
    width: 100%;
    display: flex;
    align-items: center;
    justify-content:center;
}

#drop-area{
    width: 100vh;
    height: 340px;
    padding: 30px;
    background: #fff;
    text-align: center;
    border-radius: 20px;
}
#img-view{
    width: 100%;
    height: 100%;
    border-radius: 20px;
    border: 2px dashed #bbb5ff;
    background: #f7f8ff;
    background-position: center;
    background-size:contain;
    background-repeat: no-repeat;
}

#img-view img{
    width: 100px;
    margin-top: 25px;
}
#img-view span{
    display: block;
    font-size: 12px;
    color: #777;
    margin-top: 15px;
}
```

7.1.3 JavaScript

//Java Script code

```
$(document).ready(function() {
    var dropArea = $("#drop-area");
    var inputFile = $("#input-file");
    var imageView = $("#img-view");

    inputFile.change(function() {
        uploadImage();
    });

    function uploadImage() {
        var imgLink = URL.createObjectURL(inputFile[0].files[0]);
        imageView.css({
            'background': '#fff',
            'background-repeat': 'no-repeat',
            'background-position': 'center',
            'background-image': 'url(' + imgLink + ')',
            'border': '0'
        });
        imageView.text("");
    }

    dropArea.on("dragover", function(e) {
        e.preventDefault();
    });

    dropArea.on("drop", function(e) {
        e.preventDefault();
        inputFile[0].files = e.originalEvent.dataTransfer.files;
        uploadImage();
    });

    $('#input-file').change(function() {
        var button = $("#uploadButton");
        if ($(this).val()) {
            button.css({
                'display': 'flex',
                'justify-content': 'center',
                'align-items': 'center',
            });
            button.show();
            $('.loader').hide();
        } else {
            button.hide();
        }
    });

    $('#uploadButton').click(function () {
        var form_data = new FormData($('#upload-file')[0]);

        // Show loading animation
        $(this).hide();
        $('.loader').show();

        // Make prediction by calling api /predict
        $.ajax({
            type: 'POST',
            url: '/submit',
            data: form_data,
            contentType: false,
            cache: false,
            processData: false,
            async: true,
            success: function (data) {
                // Get and display the result
                $('.loader').hide();
                $('#result').fadeIn(600);
                $('#result').text(data);
                console.log('JS/MODEL.JS : Successfully Predicted Output!');
            },
        });
    });
});
```

7.2 Backend

7.2.1 python

In the Brain tumor detection project, Python serves as the primary programming language, facilitating various tasks such as data preprocessing, model training, web development (using Flask), and model deployment. Here's how Python is utilized in different aspects of your project:

1. **Data Preprocessing**: Python's libraries such as TensorFlow, NumPy, and PIL (Python Imaging Library) are employed to preprocess the MRI images before feeding them into the machine learning model. This preprocessing may involve tasks like resizing, normalization, and converting images into arrays.

2. **Model Training**: Python, with frameworks like TensorFlow and Keras, is used to design, train, and evaluate the convolutional neural network (CNN) model for brain tumor detection. TensorFlow provides the computational backend, while Keras offers a high-level interface for building neural networks.

3. **Model Deployment**: After training, the trained model is saved in the Hierarchical Data Format (HDF5) using Python's **save** method from the Keras library. This allows for easy retrieval and deployment of the model within the Flask web application.

4. **Web Development**: Python's Flask framework is utilized for building the web application that enables users to interact with the brain tumor detection model through a user-friendly interface. Flask provides the necessary routing, request handling, and templating features to create dynamic web pages.

5. **Integration**: Python facilitates the integration of different components of the project. For instance, it integrates the machine learning model with the Flask web application, allowing users to upload MRI images, obtain predictions, and visualize results seamlessly.

7.i) Python Use Cases

7.2.2 Integration with Flask

1. **Importing Libraries**: The script starts by importing necessary libraries such as TensorFlow, NumPy, Flask, PIL (Python Imaging Library), cv2 (OpenCV), and Keras.
2. **Loading the Model**: The pre-trained brain tumor detection model is loaded using Keras's **load_model** function from the **keras.models** module. The model file is assumed to be named **model2.h5** and located in the **Model** directory.
3. **Defining Helper Functions**:
   - **get_className(prediction)**: This function takes the prediction index as input and returns the corresponding class name indicating the type of brain tumor detected.
   - **predict(img)**: This function takes the path to an image file as input, preprocesses the image, makes a prediction using the loaded model, and returns the predicted class index.
4. **Setting Up Flask App**:
   - An instance of the Flask class is created with the name **app**.
   - The model is loaded into memory when the Flask app starts.
   - A route for the home page (/), a route for the model playground (**/model**), a route for the contact page (**/contact**), and a route for prediction (**/predict**) are defined.
5. **Route Functions**:
   - **home()**: Renders the home.html template.
6. **model_page()**: Renders the model_playground.html template.
   - **contact()**: Renders the contact section of the home page.
   - **upload()**: Handles the file upload and prediction process. When a POST request is received with an uploaded image file, it saves the file, calls the **predict()** function to get the prediction, and returns the result.
7. **Running the Flask App**:
   - The script checks if it is being run directly (**__name__ == '__main__'**) and then starts the Flask app using **app.run()**.

```
import os
import tensorflow as tf
import numpy as np
from tensorflow.keras.preprocessing import image
from tensorflow.keras.preprocessing.image import load_img, img_to_array
from PIL import Image
import cv2
from keras.models import load_model
from flask import Flask, request, render_template
from werkzeug.utils import secure_filename

app = Flask(__name__)
model =load_model('/Users/model/model.h5')
```

```
print('Model loaded. Check http://127.0.0.1:5000')


def get_className(prediction):
    if prediction==0:
        return "Glioma Brain Tumor Detected"
    elif prediction==1:
        return "Meningioma Brain Tumor Detected"
    elif prediction==2:
        return "No Brain Tumor Detected"
    else:
        return "Pituitary Brain Tumor Detected"



def predict(img):
    test_image=load_img(img,target_size=(150,150))
    test_image.resize((150,150))
    image = img_to_array(test_image)
    image = image / 255.0
    image = np.expand_dims(image, axis = 0)
    result = np.argmax(model.predict(image),axis=1)
    return result
```

7.2.3 Handling Client Requests

In Flask, routes are defined using decorators, which specify URL patterns and HTTP methods that trigger specific functions. When a client makes a request to a route, Flask invokes the corresponding function, allowing developers to process the request data and generate a response. For example, in the provided code, the '/submit' route handles POST requests containing image files uploaded by clients. It extracts the file from the request, saves it to a specified location, and passes it to the prediction function.

```
@app.route('/', methods=['GET'])
def home():
    return render_template('index.html')

@app.route('/submit', methods=['GET', 'POST'])
def upload():
    if request.method == 'POST':
        #request.form
        f = request.files['file']
        basepath = os.path.dirname(__file__)
        file_path = os.path.join(
            basepath, 'uploads', secure_filename(f.filename))
        f.save(file_path)
        value=predict(file_path)
        r=get_className(value)
        return r

    return None #render_template('index.html',result=r)
```

7.2.4 Handling Server Response

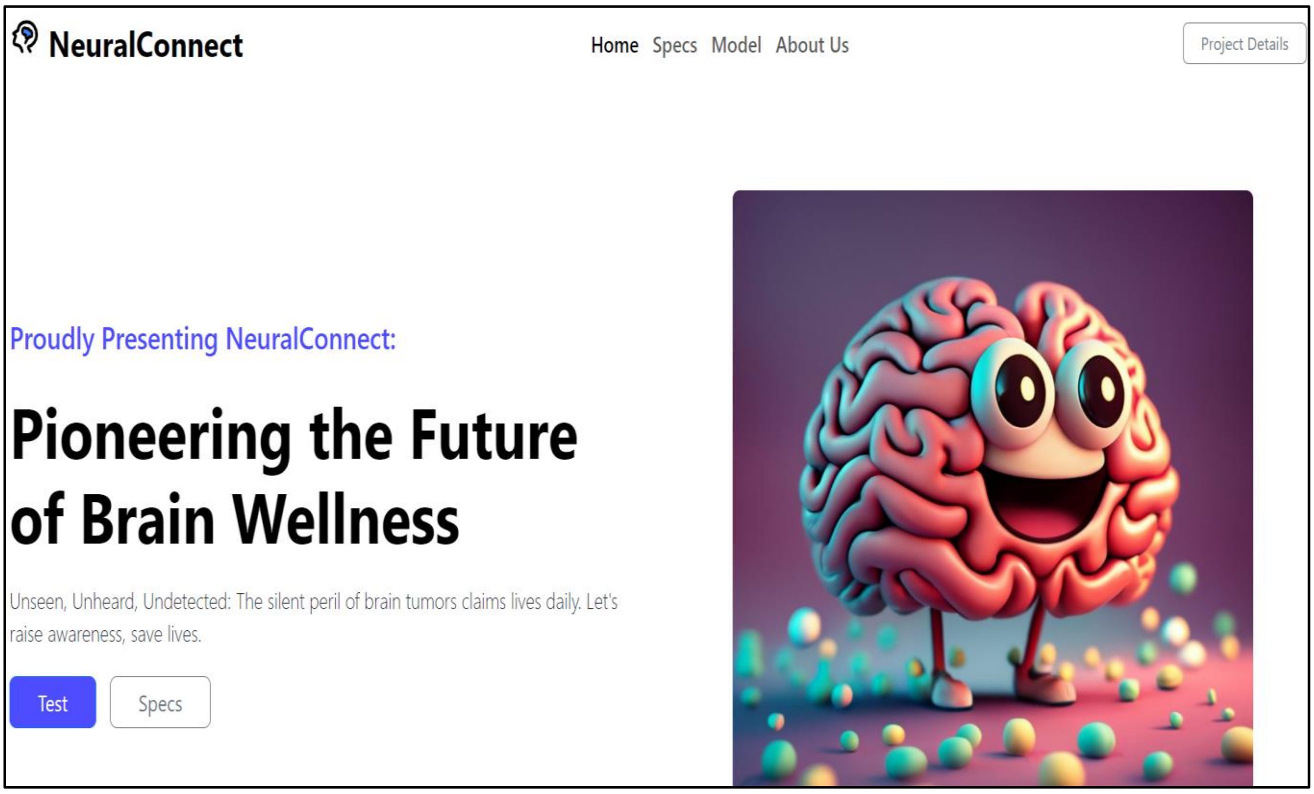
Once the server processes a client request, it generates a response to send back. This response can include HTML content, JSON data, or other types of data based on the application's requirements. In the code snippet, after processing the uploaded image, the server returns the prediction result. This response is sent back to the client, which can then display it to the user or perform further actions based on the result.

Flask's simplicity and flexibility make it an excellent choice for building web applications that require seamless integration with Python code. With its lightweight architecture and extensive documentation, Flask empowers developers to create robust and scalable web applications efficiently.

```
if __name__ == '__main__':
    app.run(debug=True)
```

Chapter 8

Output



NeuralConnect

Home Specs Model About Us

Project Details

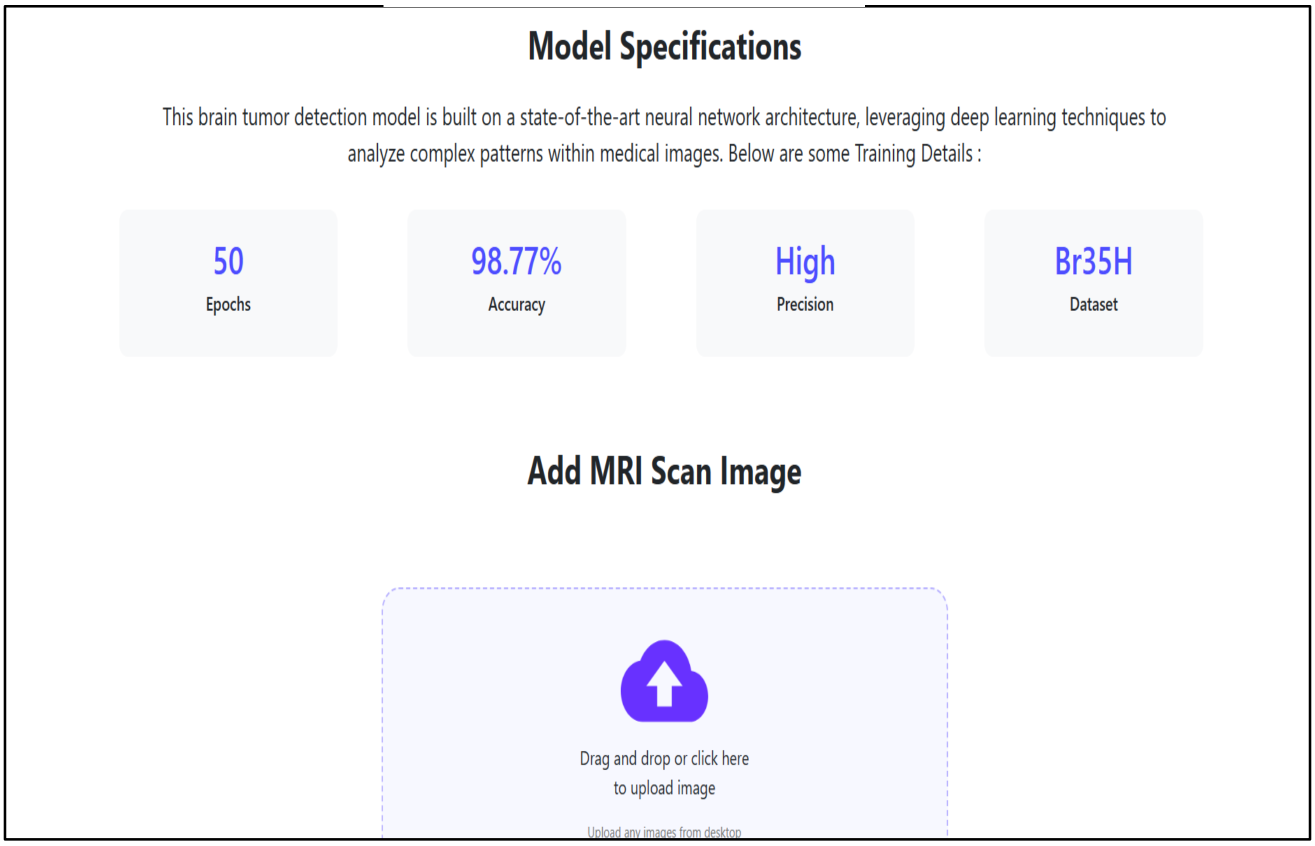
Proudly Presenting NeuralConnect:

Pioneering the Future of Brain Wellness

Unseen, Unheard, Undetected: The silent peril of brain tumors claims lives daily. Let's raise awareness, save lives.

Test Specs

8.i) Output-1



Model Specifications

This brain tumor detection model is built on a state-of-the-art neural network architecture, leveraging deep learning techniques to analyze complex patterns within medical images. Below are some Training Details :

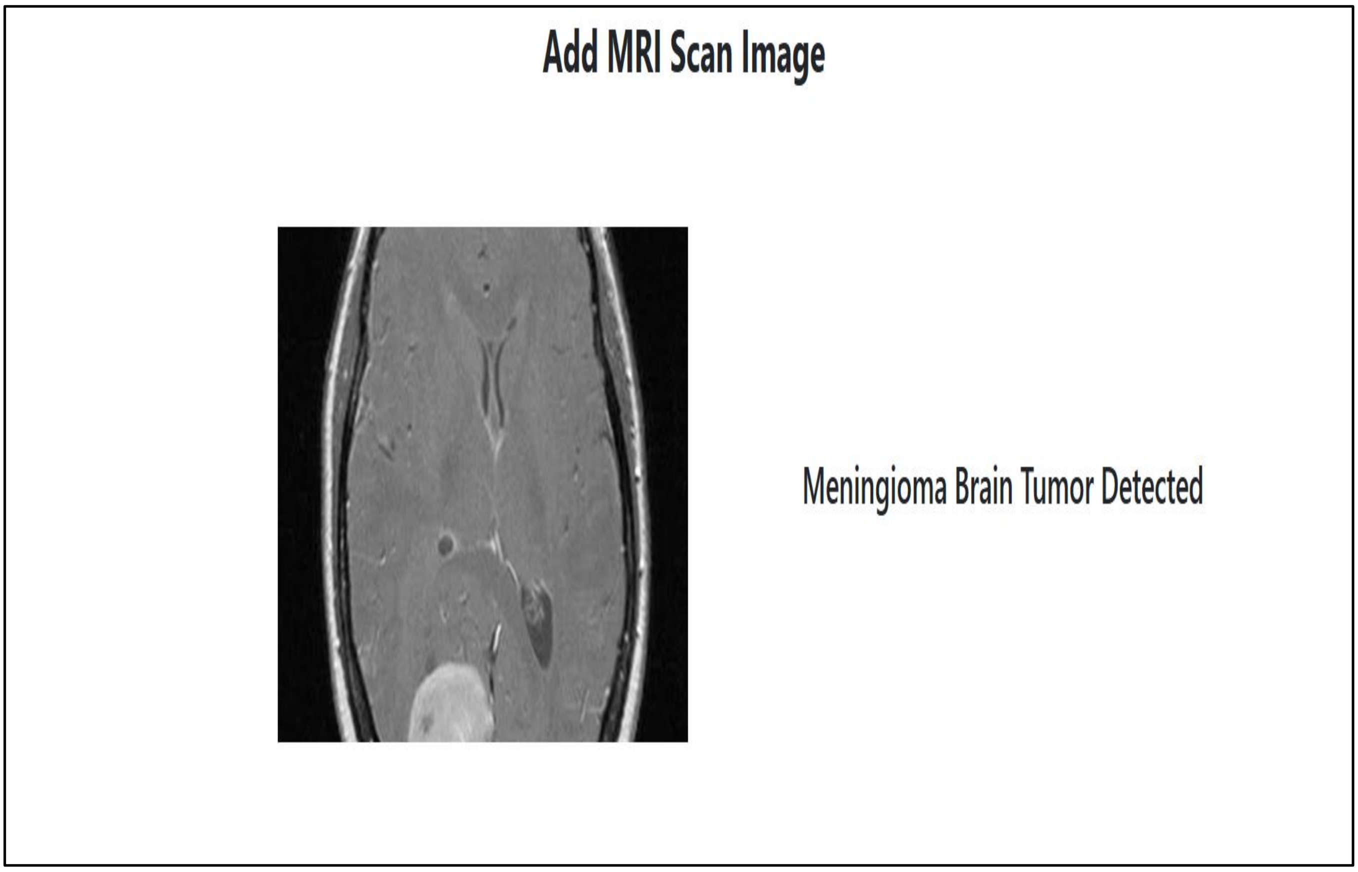
50	98.77%	High	Br35H
Epochs	Accuracy	Precision	Dataset

Add MRI Scan Image

Drag and drop or click here to upload image

Upload any images from desktop

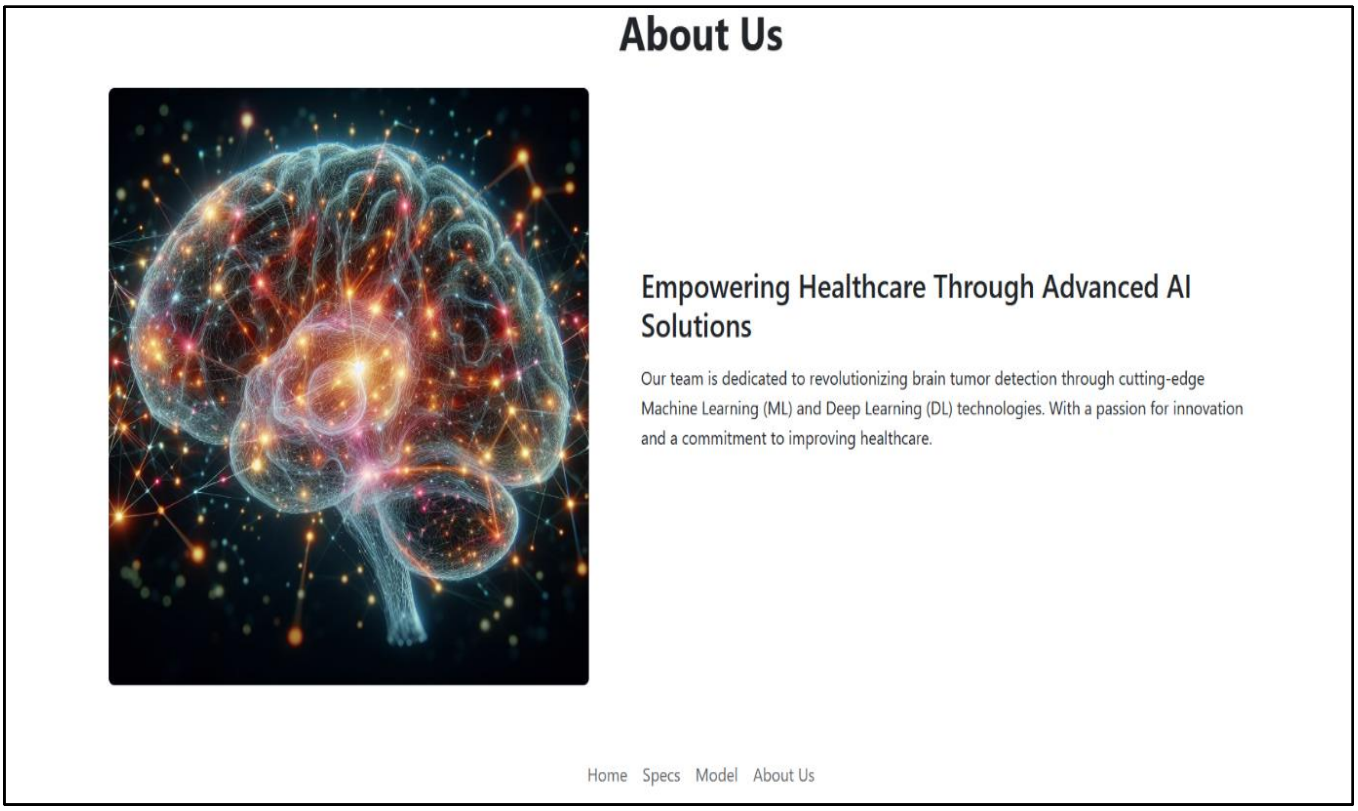
8.ii) Output-2



Add MRI Scan Image

Meningioma Brain Tumor Detected

8.iii) Output-3



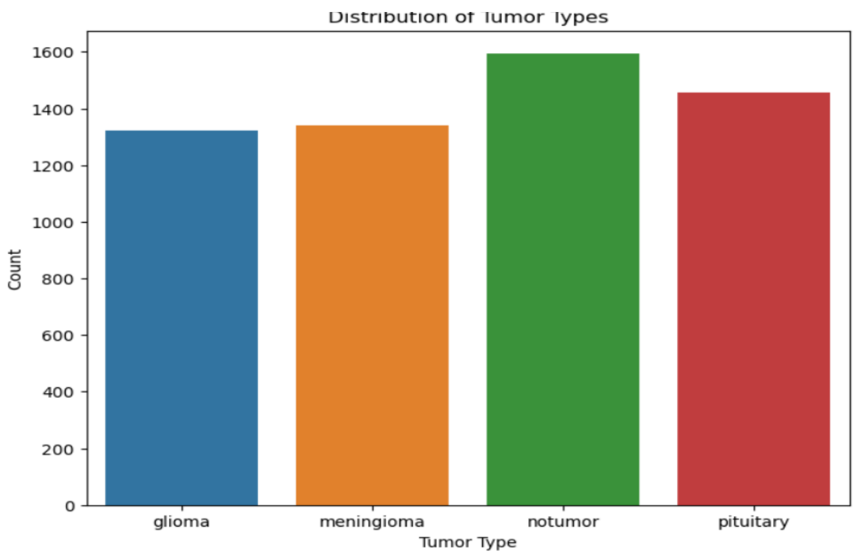
About Us

Empowering Healthcare Through Advanced AI Solutions

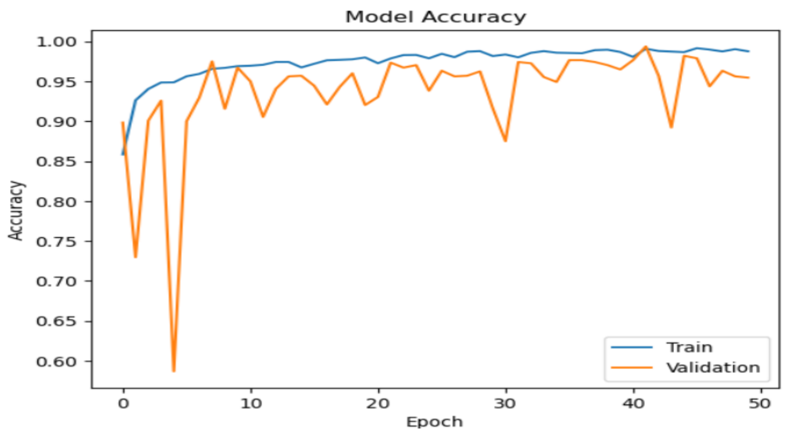
Our team is dedicated to revolutionizing brain tumor detection through cutting-edge Machine Learning (ML) and Deep Learning (DL) technologies. With a passion for innovation and a commitment to improving healthcare.

8.iv) Output-4

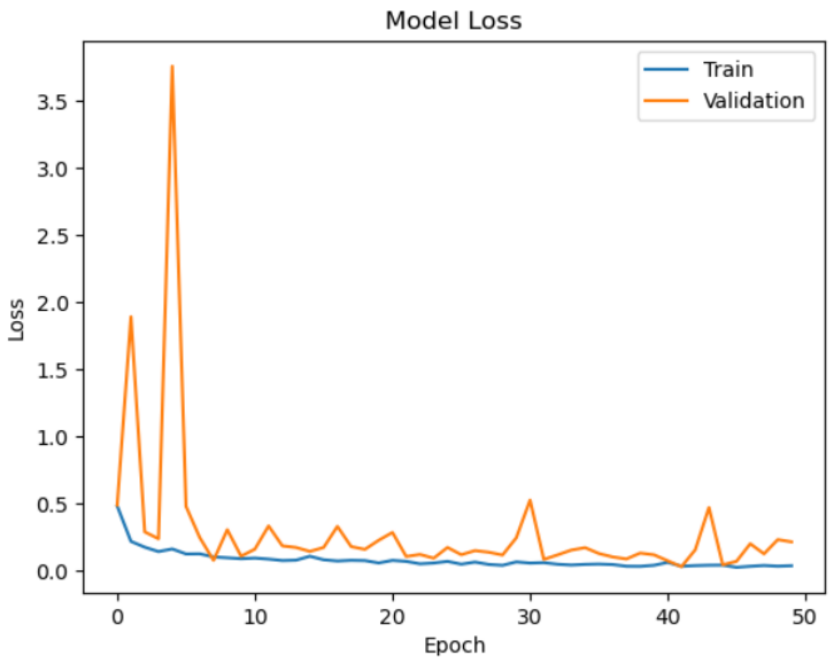
8.v) Output-5



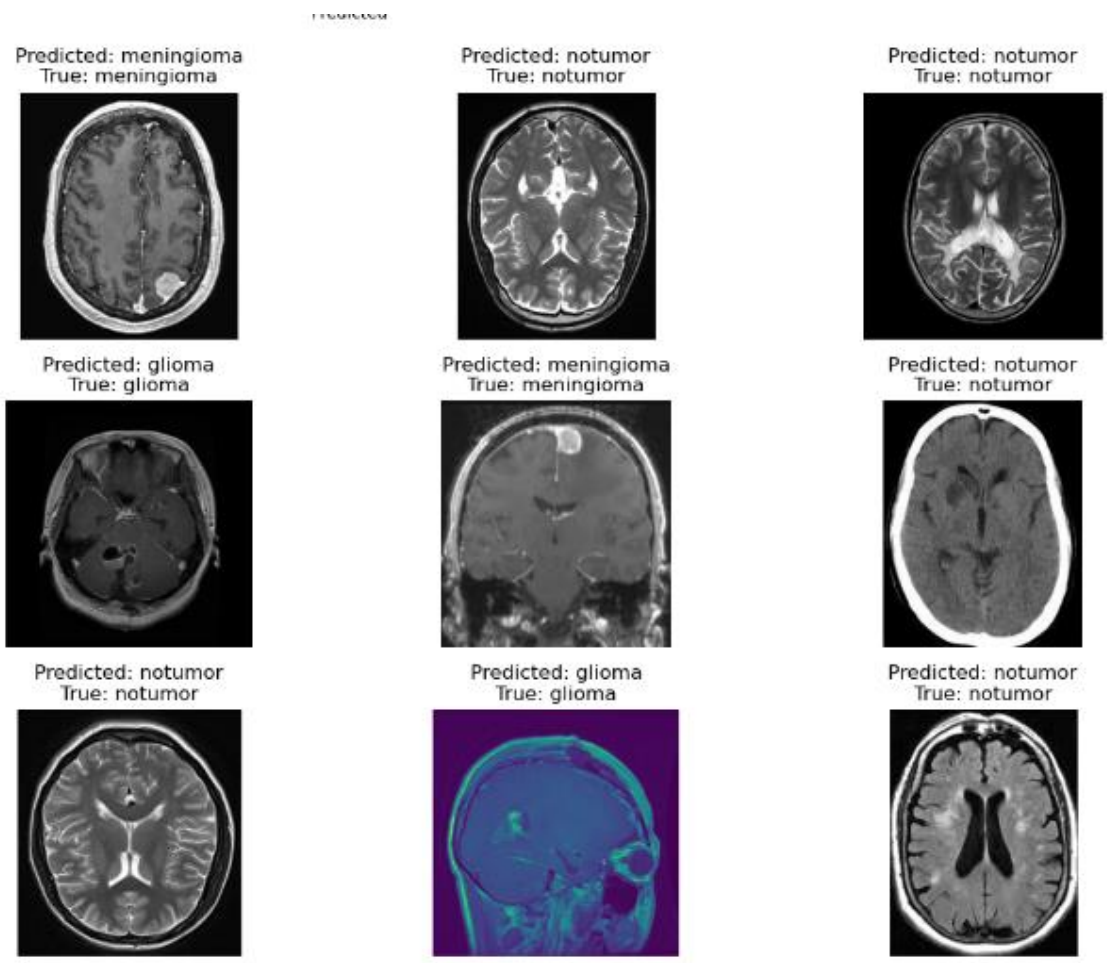
8.vi) Output-6



8.vii) Output-7



8.viii) Output-8



8.ix) Output-9

Chapter 9

Conclusion and Future Scope

1. Conclusion

In conclusion, this project aims to redefine the approach to brain tumor detection and classification through the integration of cutting-edge technologies and methodologies. Leveraging Convolutional Neural Networks (CNNs) and Transfer Learning, particularly utilizing the MobileNet architecture, the project strives to meet the critical need for early and accurate diagnosis of brain tumors.

The developed system demonstrates remarkable accuracy in classifying brain tumors into specific types, including glioma, meningioma, pituitary, or identifying cases with no tumor presence. This level of classification accuracy is pivotal for healthcare professionals, enabling them to make swift and accurate diagnoses, leading to timely medical interventions and improved patient outcomes.

Interdisciplinary collaboration lies at the heart of this project, bringing together expertise from various domains, including medical professionals, data scientists, and computer engineers. This collaborative effort ensures that the developed solution not only meets technical requirements but also aligns with clinical standards and best practices in neuroimaging and oncology.

Through rigorous testing and evaluation methodologies, including the assessment of metrics such as accuracy, precision, recall, and F1-score, the project showcases the robustness and reliability of the developed system. These evaluation metrics serve as benchmarks for assessing the model's performance on unseen data, providing valuable insights into its generalization capabilities and real-world applicability.

In summary, this project represents a significant advancement in medical imaging and healthcare technology. By offering a comprehensive solution for brain tumor detection and classification, the system has the potential to significantly impact patient care, clinical decision-making processes, and ultimately, contribute to saving lives. Its unique approach and high accuracy make it a standout innovation in the field, promising a brighter future for brain tumor diagnosis and treatment.

2. Future Scope

Looking ahead, there are several avenues for further development and enhancement of the brain tumor detection and classification system:

1. **Improved Model Architectures**: Continuously refining and optimizing the deep learning models used for tumor detection and classification can lead to even higher levels of accuracy and performance. Exploring advanced architectures or incorporating ensemble methods could potentially yield superior results.

2. **Expansion of Dataset**: Expanding the dataset with more diverse and representative brain MRI images can enhance the model's ability to generalize across different patient demographics, imaging modalities, and tumor variations. Incorporating data augmentation techniques can also contribute to better model robustness.

3. **Incorporation of Multi-Modal Data**: Integrating additional data sources, such as clinical data, genetic information, or other imaging modalities like functional MRI (fMRI) or diffusion tensor imaging (DTI), can provide richer insights into tumor characteristics and improve diagnostic accuracy.

4. **Real-Time Deployment**: Developing the system into a real-time application that can analyze MRI scans as they are acquired in clinical settings would greatly streamline the diagnostic

process. This would involve optimizing the model for inference speed and deploying it on edge devices or cloud platforms.

5. **Clinical Validation and Regulatory Approval**: Conducting extensive clinical validation studies to evaluate the system's performance in real-world healthcare settings is crucial for gaining regulatory approval and widespread clinical adoption. Collaborating with medical institutions and obtaining necessary approvals will be essential for this phase.
6. **Integration with Healthcare Systems**: Integrating the developed solution with existing healthcare information systems, such as Picture Archiving and Communication Systems (PACS) or Electronic Health Records (EHR), can facilitate seamless workflow integration and enable efficient communication of diagnostic results to healthcare providers.
7. **Continuous Monitoring and Feedback**: Implementing mechanisms for continuous monitoring and feedback from healthcare professionals can help identify areas for improvement and refine the system based on real-world usage and feedback.

Overall, the future scope of the project involves advancing the system to meet the evolving needs of the medical community, improving diagnostic accuracy, and ultimately, making a positive impact on patient care and outcomes in the field of neuroimaging and oncology.

Chapter 10

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- **GitHub - TensorFlow Models:** https://github.com/tensorflow/models/blob/master/official/README.md
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