A Project Report On

BRAIN TUMOR PREDICTION USING DEEP LEARNING NETWORK

Submitted in partial fulfillment of the requirement for the 8^{th} semester

Bachelor of Engineering

in

Computer Science and Engineering

DAYANANDA SAGAR COLLEGE OF ENGINEERING

(An Autonomous Institute affiliated to VTU, Belagavi, Approved by AICTE & ISO 9001:2015 Certified)

Accredited by National Assessment & Accreditation Council (NAAC) with ‘A’ grade

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Department of Computer Science and Engineering

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CERTIFICATE

This is to certify that the project entitled **Brain Tumor Prediction using Deep Learning Network** is a bonafide work carried out by **Yukta N. Shettigar [1DS19CS197]**, **Bhargavi S. [1DS19CS198], Keerthana K. [1DS19CS721]** and **K. R. Divyashree [1DS19CS722]** in partial fulfillment of 8^{th} semester, Bachelor of Engineering in Computer Science and Engineering under Visvesvaraya Technological University, Belgaum during the year 2022-23.

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1.......................... ....

2............................ ....

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We are pleased to have successfully completed the project **Brain Tumor Prediction using Deep Learning Network**. We thoroughly enjoyed the process of working on this project and gained a lot of knowledge doing so.

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ABSTRACT

Brain tumor detection and diagnosis play a critical role in the timely treatment and management of patients. Traditional diagnostic techniques frequently rely on the manual interpretation of medical images, which can result in subjective outcomes and potential human errors. To overcome these limitations, a novel approach has been proposed for predicting brain tumors that integrates a **Deep Learning Network** — specifically **ResNet50** — with a **Web Application** using **HTML**, **CSS** for frontend, and **Flask** for backend framework. The proposed system leverages the power of deep learning algorithms to automate the detection and classification of brain tumors from magnetic resonance imaging (MRI) scans. ResNet-50, a state-of-the-art convolutional neural network (CNN) architecture, is employed as the backbone for feature extraction and classification. The dataset utilized for training and evaluation consists of a large collection of MRI images with labeled tumor regions. The images are pre-processed to enhance contrast and remove noise, ensuring optimal input for the deep learning network. A supervised learning approach is used to train the ResNet-50 model, where the network learns to identify and differentiate between healthy brain tissues and tumor regions. Here, brain tumors are classified into four main categories based on their characteristics and origin of cells namely - **Glioma**, **Mengioma**, **Pitutary**, **No Tumor**. To provide a user-friendly interface for the trained model, Flask, a Python-based web framework, is integrated. Users can upload their MRI scans through the web interface, and the integrated system will process the images, perform tumor prediction, and present the results to the user. Evaluation of the proposed system involves assessing its **Accuracy**, **Precision**, **Sensitivity**, **F1 Score**, **AUC** and overall performance using a separate test dataset. The test accuracy attained in this work was around **98%**. The results demonstrate the effectiveness of the proposed approach in accurately predicting brain tumor presence and classifying tumor types.

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Chapter 1

INTRODUCTION

1.1 Human Brain and Tumor Characteristics

1.1.1 Structure and Functions of the Brain

The brain is an intricate organ that plays a vital role in regulating our thoughts, emotions, and physical processes. It is divided into different regions as depicted in Figure 1.1, each of which is responsible for specific functions. The brain is made up of three main components; **Cerebrum**, **Cerebellum**, and **Brainstem**, which are further divided into various lobes and structures.

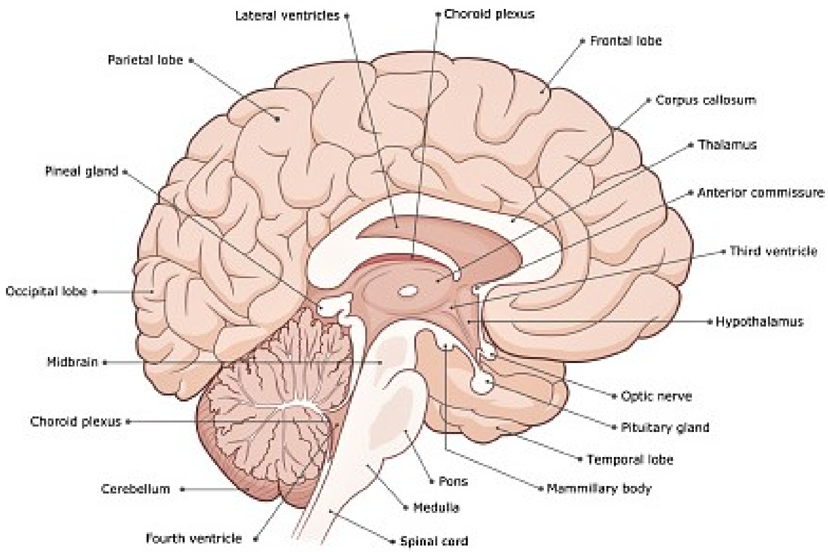


Figure 1.1: Structure of Human Brain

The Cerebrum is the largest part of the brain and is responsible for cognitive functions such as reasonining, memory, and language. It is separated into the left and right hemispheres, which are connected by a bundle of nerve fibers called the **Corpus Callosum**.

Each hemisphere is further divided into lobes: the **Frontal Lobe**, **Parietal Lobe**, **Temporal Lobe**, and **Occipital Lobe**. These lobes control different facets of our behavior, perception, and sensory processing.

The Cerebellum, located at the back of the brain, is primarily involved in coordinating movements, maintaining balance, and posture. It receives information from the sensory systems, the spinal cord, and other parts of the brain to ensure smooth and coordinated muscle movements.

The Brainstem, located at the base of the brain, connects the brain to the spinal cord and controls fundamental functions such as breathing, heart rate, and blood pressure. Additionally, it serves as a conduit for nerve signals traveling between the brain and the rest of the body.

1.1.2 Overview of Brain Tumors and their Impact on Health

Brain tumors are abnormal growths that form within the brain or its surrounding tissues. They can develop either from other brain structures or from various cell types, such as glial cells, which support and nourish the neurons.

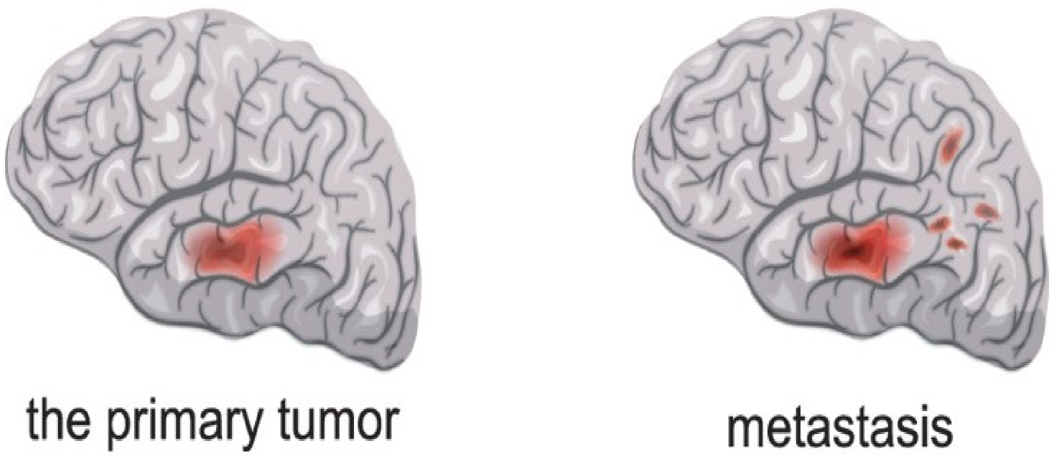


Figure 1.2: Types of Brain Tumor

Brain tumours can be divided into two basic categories: **Primary Tumors** and **Secondary Tumors**, as shown in Figure 1.2. Primary brain tumors originate within the brain, while Secondary tumors, commonly referred to as **Metastatic** Tumors, originate from cancer cells that have spread to the brain from other parts of the body. Brain tumors can vary in their characteristics and behavior. They can be **Benign** (non-cancerous) or **Malignant** (cancerous). Benign tumors tend to grow slowly, have well-defined borders, and do not invade surrounding brain tissue. Malignant tumors, on the other hand, are more aggressive, can grow rapidly, and have the potential to invade nearby healthy tissue.

Figure 1.3 presents some of the common types of Brain Tumor:

(a) **Meningioma Tumor**: Meningiomas are tumors that develop in the meninges, which are the protective membranes that cover the brain and spinal cord. These tumors are typically slow-growing and are often benign, meaning they are non-cancerous. However, in some cases, meningiomas can be malignant and have the potential to spread to other parts of the body. Meningiomas originate from the cells of the meninges and can put pressure on the adjacent brain tissue, leading to various symptoms depending on their size and location. Common symptoms include headaches, seizures, changes in vision or hearing, and neurological deficits.

(b) **Glioma Tumor**: Gliomas are a type of tumor that originates in the glial cells, which are cells that provide support and protection to the nerve cells in the brain. Gliomas can occur in various parts of the brain and can be classified as either benign (non-cancerous) or malignant (cancerous). Malignant gliomas, such as glioblastoma, are particularly aggressive and can rapidly grow and spread to nearby brain tissues. These tumors can cause significant damage to the normal brain tissue and interfere with its functions, leading to neurological symptoms such as seizures, cognitive impairments, personality changes, and motor deficits. Treatment options for gliomas include surgery, radiation therapy, and chemotherapy.

(c) **Pituitary Tumor**: Pituitary tumors, also known as **Pituitary Adenomas**, develop in the pituitary gland, which is a small gland located at the base of the brain. These tumors can be either non-cancerous or benign adenomas. The pituitary gland plays a crucial role in regulating various hormonal functions in the body. Depending on the type of cells involved, pituitary tumors can affect hormone production and cause hormonal imbalances. Symptoms may vary depending on the size and hormone-secreting activity of the tumor and can include hormonal disturbances, vision problems, headaches, and fatigue.

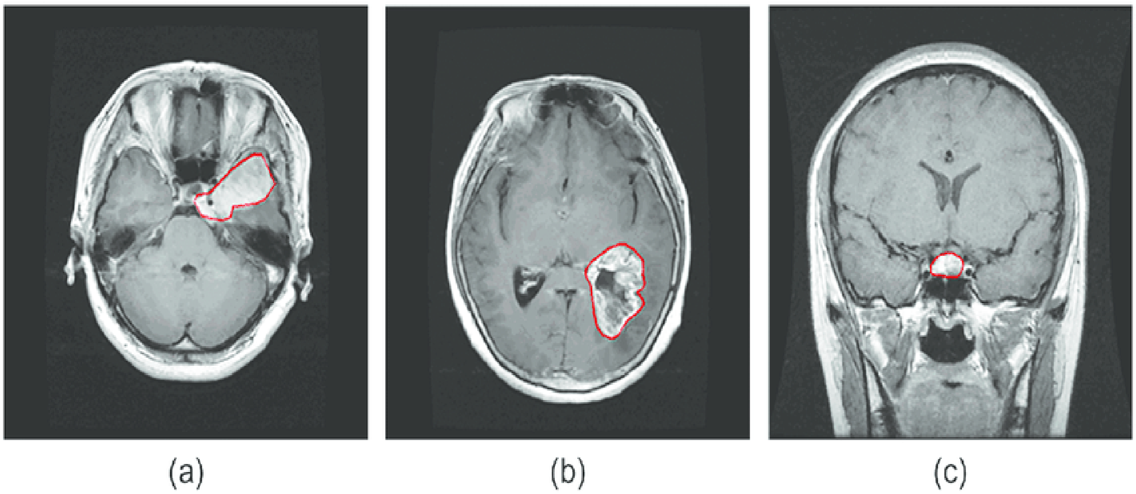


Figure 1.3: (a) Meningioma Tumor; (b) Glioma Tumor; and (c) Pituitary Tumor. Red lines specify the tumor border.

The adverse impact of brain tumors on health could vary depending on factors such as the size, location, and rate of growth of the tumor. Brain tumors can disrupt the normal functioning of the brain by exerting pressure on surrounding structures, interfering with neurological pathways, and causing inflammation. This can lead to a wide range of symptoms, including headaches, seizures, cognitive impairment, motor deficits, sensory alterations, and personality changes. In severe cases, brain tumors can be life-threatening. Therefore, precise identification and segmentation of brain tumors are crucial for effective treatment planning.

1.2 Challenges and Importance in Diagnosing Brain Tumors

1.2.1 Challenges in Diagnosing and Treating Brain Tumors

Brain tumor diagnosis and treatment are challenging for both patients and medical professionals. The challenges that arise include:

(i) **Non-specific symptoms**: Brain tumors often present with symptoms that can be non-specific and overlap with other neurological conditions. This can lead to delays in diagnosis and treatment initiation.

(ii) **Complex imaging interpretation**: The interpretation of brain imaging, such as magnetic resonance imaging (MRI) or computed tomography (CT) scans, requires expertise. Differentiating between tumor tissue and normal brain tissue can be challenging due to variations in tumor characteristics and potential imaging artifacts.

(iii) **Invasive biopsy procedures**: Confirming the presence of a brain tumor usually involves obtaining a tissue sample through surgical biopsy. These procedures carry inherent risks and may not be feasible in certain cases, such as tumors located in critical or inaccessible areas of the brain.

(iv) **Treatment limitations**: The treatment of brain tumors depends on factors such as tumor type, location, and stage. Treatment options may include surgery, radiation therapy, chemotherapy, or a combination of these modalities. However, the effectiveness of treatment can be limited by the infiltrative nature of some tumors, the blood-brain barrier restricting drug delivery, and potential damage to healthy brain tissue.

1.2.2 Importance of Early Detection and Accurate Diagnosis

Early detection and accurate diagnosis of brain tumors are crucial for several reasons:

(i) **Treatment efficacy**: Early detection allows for timely intervention, which can improve treatment outcomes. It provides a greater chance of successfully removing the tumor or controlling its growth, resulting in improved patient survival rates and quality of life.

(ii) **Treatment planning**: Accurate diagnosis helps in determining the most appropriate treatment strategy for each patient. This may involve selecting the optimal surgical approach, deciding on the need for adjuvant therapies such as radiation or chemotherapy, and monitoring treatment response.

(iii) **Patient management**: Early diagnosis enables healthcare providers to manage symptoms and support patients throughout the treatment journey. It allows for the implementation of supportive care measures, such as pain management, seizure control, and rehabilitation services, to enhance the patient's well-being and overall quality of life.

(iv) **Research and advancements**: Early diagnosis contributes to a better understanding of brain tumors and facilitates research efforts aimed at developing new treatment approaches, innovative therapies, and improved diagnostic tools. It also allows for the inclusion of patients in clinical trials, providing opportunities for access to novel treatments and advancements in care.

Overall, early detection and accurate diagnosis of brain tumors are crucial for improving patient outcomes, optimizing treatment planning, and driving advancements in the field of brain tumor research and care.

1.3 Overview of Manual Segmentation

1.3.1 Manual Segmentation

Manual segmentation has several limitations and challenges. Firstly, it is a time-consuming process, particularly for large or complex tumors. The need for expert intervention and the intricate nature of brain anatomy can extend the time required for accurate manual segmentation. This can lead to delays in diagnosis, treatment planning, and subsequent patient management.

Another challenge associated with manual segmentation is its subjective nature. Different observers may interpret and delineate tumor boundaries differently, leading to inter-observer variability. This variability can introduce inconsistencies in the segmentation results, potentially impacting treatment decisions and patient outcomes. Furthermore, the manual segmentation process is prone to human errors and fatigue, which can further affect the accuracy and reliability of the results.

Therefore, the development of automated and accurate segmentation methods using advanced techniques such as deep learning is essential for improving brain tumor diagnosis and treatment planning.

1.3.2 Need for Semantic Segmentation

Semantic segmentation is an advanced technique in image analysis that aims to automatically classify and segment different objects or regions within an image based on their semantic meaning. In the context of medical imaging, semantic segmentation involves automatically identifying and delineating specific structures or abnormalities, such as brain tumors, without the need for manual intervention.

The need for semantic segmentation in the context of brain tumors arises from several reasons:

(i) **Efficiency and Time-Saving**: Manual segmentation can be a laborious and time-consuming process. Automated semantic segmentation techniques, based on machine learning algorithms and deep learning models, offer the potential to accelerate the segmentation process, reducing the time and effort required by healthcare professionals.

(ii) **Consistency and Standardization**: Manual segmentation is subjective and can vary among different observers. Semantic segmentation algorithms, once trained and validated, provide consistent and standardized results. This reduces inter-observer variability and ensures greater consistency in tumor delineation, leading to more reliable and reproducible measurements.

(iii) **Accuracy and Precision**: Semantic segmentation techniques leverage the power of advanced algorithms and models to achieve high levels of accuracy and precision in tumor detection and delineation. These techniques can effectively capture intricate tumor boundaries, including irregular shapes and subregions, which might be challenging to consistently achieve through manual segmentation.

(iv) **Scalability and Generalization**: With the increasing volume of medical imaging data, there is a growing need for scalable and generalizable segmentation approaches. Semantic segmentation algorithms can be trained on large datasets and generalize well to new cases, enabling their application in different clinical settings and facilitating broader access to accurate and efficient tumor segmentation.

(v) **Integration with Decision Support Systems**: Semantic segmentation results can be seamlessly integrated into decision support systems and computer-aided diagnosis tools. This integration allows for quantitative analysis, extraction of meaningful imaging biomarkers, and generation of comprehensive reports, assisting healthcare professionals in making informed decisions regarding treatment planning and patient management.

Semantic segmentation addresses the limitations of manual segmentation by providing automated, efficient, accurate, and consistent tumor delineation. It holds great promise in enhancing the diagnosis, treatment planning, and monitoring of brain tumors, ultimately improving patient care and outcomes.

1.4 Overview of Deep Learning

1.4.1 Deep Learning and its Application in Various Fields

Deep learning is a subfield of machine learning that focuses on the development and application of **Artificial Neural Networks** (Figure 1.4) inspired by the structure and function of the human brain. It is characterized by the use of deep neural networks with multiple layers, enabling the learning of hierarchical representations from complex data.

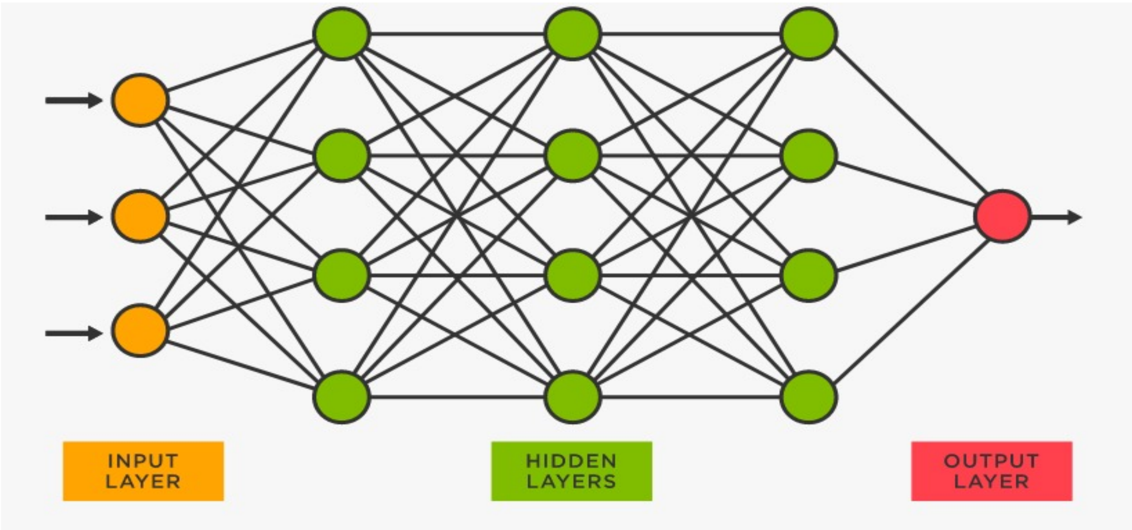


Figure 1.4: Architecture of Neural Network

Deep learning has gained significant attention and achieved remarkable success in various fields, including computer vision, natural language processing, speech recognition, and robotics. Its ability to automatically learn features and patterns from large datasets has revolutionized the way complex problems are approached and solved. In the context of medical image analysis, deep learning has emerged as a powerful tool for extracting meaningful information and making accurate predictions from medical images such as MRI, CT scans, and histopathology slides. It has the potential to assist healthcare professionals in tasks such as disease diagnosis, tumor segmentation, treatment planning, and prognosis.

1.4.2 Relevance of Deep Learning in Medical Image Analysis

The relevance of deep learning in medical image analysis stems from its capability to automatically learn complex image representations. Traditional image analysis techniques often require the design and extraction of handcrafted features, which can be time-consuming and limited in capturing the full complexity of medical images. Deep learning, on the other hand, can automatically learn hierarchical representations directly from the raw image data, allowing for more comprehensive and nuanced analysis.

Deep learning techniques for medical image analysis typically involve the use of convolutional neural networks (CNNs). CNNs are well-suited for analyzing images due to their ability to exploit local spatial correlations through convolutional operations and hierarchical feature learning through multiple layers.

1.5 Real – World Applications

(1) **Medical Diagnosis and Treatment Planning**: Accurate prediction of brain tumors using deep learning plays a crucial role in medical diagnosis and treatment planning. By utilizing the ResNet50 deep learning network, the system can detect brain tumors early, enabling timely interventions. Medical professionals can rely on the system's predictions to make informed decisions about patient care, such as determining the presence, location, and classification of brain tumors. This information is vital for developing targeted treatment plans and optimizing patient outcomes.

(2) **Clinical Decision Support**: The brain tumor prediction system serves as a valuable tool for clinicians by providing additional insights and objective information to support clinical decision-making. Clinicians can use the system's predictions to validate their own assessments and enhance diagnostic accuracy. The system's reliable predictions aid in confirming or refining initial diagnoses, enabling medical professionals to make more confident decisions about patient management and treatment strategies.

(3) **Radiology and Imaging**: Integrating deep learning algorithms with brain imaging techniques revolutionizes radiological practices. The system automates the detection and segmentation of brain tumors, reducing reliance on manual interpretation and improving efficiency. Radiologists can leverage the system as a reliable and efficient tool for analyzing brain images, enhancing their workflow and allowing them to focus on more complex cases. This technology can potentially expedite the diagnostic process and improve overall patient care in radiology departments.

(4) **Research and Development**: The project contributes to the advancement of medical imaging and tumor diagnosis research. By evaluating the effectiveness of deep learning algorithms, specifically ResNet50, for brain tumor prediction, the project provides valuable insights and methodologies for further improvement. Researchers can use the project's findings to explore novel approaches, refine existing algorithms, and enhance the overall accuracy and efficiency of brain tumor detection and classification.

(5) **Personalized Medicine**: Accurate prediction and classification of brain tumors facilitate personalized treatment plans for patients. The system provides insights into specific tumor characteristics, such as size, location, and aggressiveness, which can help tailor therapies accordingly. Personalized medicine improves patient outcomes by optimizing treatment approaches and minimizing unnecessary interventions. The brain

tumor prediction system contributes to the advancement of personalized medicine by providing reliable information to guide individualized patient care.

(6) **Education and Training**: The project serves as an educational tool for medical students and professionals interested in medical imaging and deep learning. It demonstrates the practical application of deep learning algorithms for medical image analysis and tumor prediction. The system's user-friendly interface and intuitive results presentation make it accessible for educational purposes. It can be used to enhance understanding of medical imaging techniques, deep learning algorithms, and their role in brain tumor detection, contributing to the education and training of future healthcare professionals.

(7) **Healthcare Management**: Efficient brain tumor prediction supports healthcare institutions in resource allocation and patient management. Timely interventions based on accurate predictions improve patient outcomes and reduce healthcare costs. By automating tumor detection and providing reliable predictions, the system enhances workflow efficiency. This allows medical staff to focus on critical tasks, streamline patient management processes, and allocate resources effectively, ultimately improving overall healthcare management.

(8) **Future Medical Technologies**: The project showcases the potential of deep learning networks, specifically ResNet50, in medical applications. It highlights the role of advanced technologies in accurate and automated brain tumor detection. The project's findings contribute to ongoing research and development efforts aimed at further enhancing medical imaging technologies. The utilization of deep learning algorithms in medical imaging has the potential to transform the field, leading to more accurate and efficient diagnosis and treatment of various diseases, not just brain tumors.

1.6 Organization of Project Report

The project report is organized as follows:

Chapter (2) discusses the problem statement and the proposed solution. The chapter also takes a look at the systems that exist today and the drawbacks they face.

Chapter (3) takes a more in-depth look at various hardware and software based solutions that exist, with a survey on existing literature available.

Chapter (4) looks at the architecture of the proposed solution with an overview of the system design, utilizing system block diagrams and data flow diagrams.

Chapter (5) dives into the Implementation of the solution, by describing the hardware and software requirements, along with dataset descriptions and implementation details.

Chapter (6) describes our testing process.

Chapter (7) looks at the obtained results.

Chapter (8) summarizes the findings, future work and conclusion of the project.

Chapter 2

PROBLEM STATEMENT AND PROPOSED SOLUTION

2.1 Problem Statement

Brain Tumor Prediction and Classification from MR images is a challenging task that requires accurate and efficient techniques. Existing approaches often lack a specific focus on this problem, resulting in lower accuracy rates and potential misdiagnosis. To overcome this limitation, this research problem aims to develop a novel solution using Deep Learning, specifically the **ResNet50 Model**, to improve the accuracy of brain tumor classification. The goal is to create a robust and reliable model that can accurately distinguish between different tumor types and provide precise predictions. By addressing this research problem, the aim is to contribute to the field of medical imaging and enhance the diagnosis of brain tumors, ultimately leading to improved patient outcomes.

2.2 Existing System

2.2.1 What is the Strategy ?

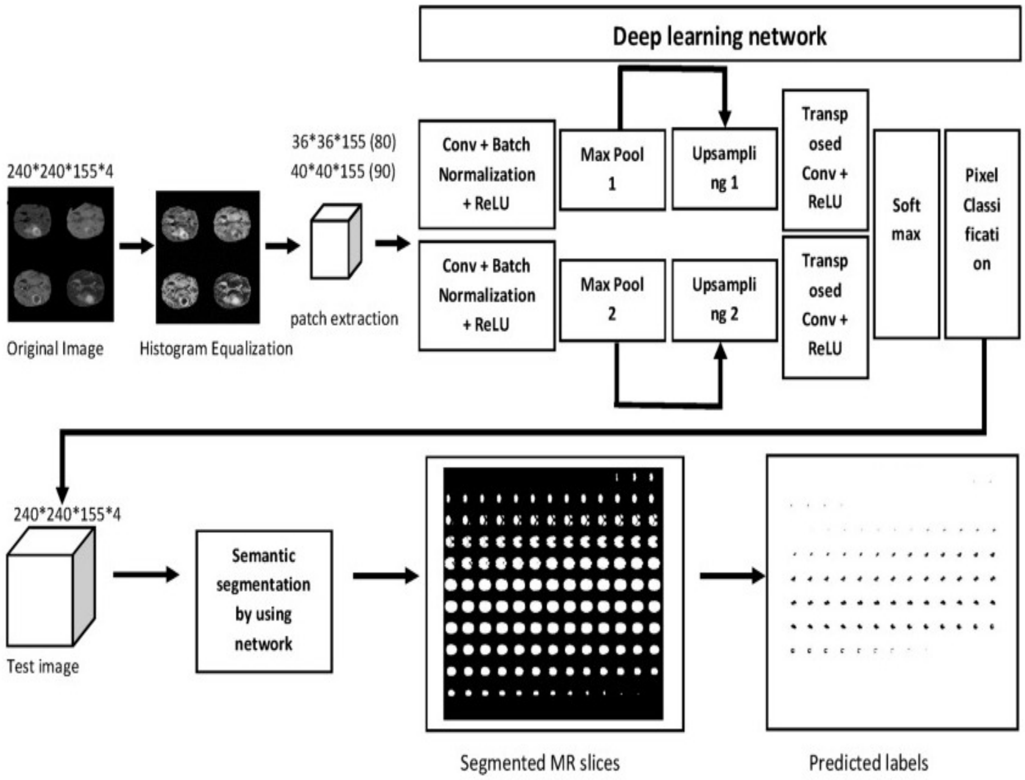


Figure 2.1: Architecture of Existing System.

The Strategy of the Existing System as displayed in Figure 2.1, involves the following stages:

(1) **Image acquisition**: BraTS dataset is used to evaluate the segmentation performance. The brain MR dataset contains 257 training images with corresponding labels and 4 different imaging modalities. As test images, 5 different MR images were used in order to apply semantic segmentation for background and tumor prediction and analyze the segmentation metrics such as mean accuracy, mean IoU, weightedIoU and meanBFScore. MR images are displayed on MATLAB, some image processing techniques like image sharpening and histogram equalization are applied.

(2) **Pre-Processing Operation**: Histogram equalization is applied to original images in order to enhance the contrast. Adaptive histogram equalization technique is employed to compute several histograms. Each of these histograms correspond a distinct section of the image and utilize from them for redistributing the lightness value of the image.

This technique enhances the definitions of the edges in each region while improving local contrast.

(3) **Feeding images to neural network**: Random patches taken or extracted from MR images are used as input and fed into the neural network. Reason for selecting these patch sizes is to optimize the deep learning network and maximize the performance of the network as much as possible.

(4) **Training process of the neural network**: Training process of this network which consists 16 layers such as convolution layers, batch normalization layers, relu layers, max pooling layers corresponding to down-sampling and for up-sampling, transposed convolution layers and relu layers were used. Softmax layer and pixel categorization layer serve as the last layers of a deep learning network.

(5) **Applying semantic segmentation to test images**: After the training process, semantic segmentation was applied to test images. The process of matching each pixel of an MR brain image with a class label, such as background and tumor, is known as semantic segmentation. It involves labeling each pixel in an image or voxel of a 3-D volume with a class. Application of a semantic segmentation by using deep learning network, classifies every pixel in an image. Predicted labels and segmented MR slices are the outputs of the semantic segmentation.

(6) **Evaluating the result of semantic segmentation**: Several distinct metrics are employed to evaluate the result of the segmentation, including:

- **Global Accuracy** - it is the ratio of correctly classified pixels to the total number of pixels without relying upon class.
- **Mean Accuracy** - it is the ratio of correctly classified pixels against total pixels for each class.
- **MeanIoU** - in terms of evaluating semantic segmentation results more accurately, IoU (Intersection over Union) metric can be used which is also defined as a "**Jaccard index**".
- **WeightedIoU** - it is the mean IoU value of all classes and it is determined with weighted mean values of number of pixels for each class.
- **MeanBFscore** - it indicates the similarity between predicted contours of each class and true contours.

- **Dice-index** - to evaluate semantic segmentation results, dice coefficient also has an important role.

(7) **3D image and label imaging with test images**: Results of semantic segmentation are displayed in the final stage. 3D imaging of whole brain, ground truth and predicted labels to compare similarity and tumor structure in terms of presenting the dimensions of tumor including width, height, and depth.

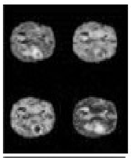
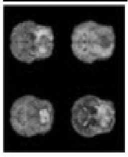
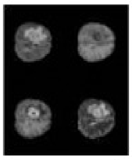
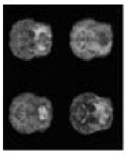
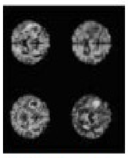
Input Image Size (240*240*155*4)	Patch Size	Patch per image	Background Prediction (%)	Tumor Prediction (%)	Mean Accuracy (%)	Mean IoU (%)	WeightedIoU (%)	MeanBFScore (%)
	36*36*155	80	99.84	87.93	93.89	84.7	99.59	94.93
	36*36*155	80	99.56	95.03	97.29	86.07	99.1	88.28
	40*40*155	90	99.71	97.83	98.77	88.12	99.45	94.85
	40*40*155	90	99.78	87.42	93.6	87.75	99.26	91.84
	40*40*155	90	99.89	90.38	95.14	88.09	99.71	94.79
Mean Values (%)			99,756	91,718	95,738	86,946	99,422	92,938

Figure 2.2: Evaluation Results of the Existing System

In terms of applying semantic segmentation by using Neural Network, two different classes were identified on MR images such as background and tumor. According to results in Figure 2.2, the **Mean Tumor Prediction** was determined as **91.72** and **Mean Background Prediction** was calculated as **99.75**. Other metrics for 5 images including **Mean Accuracy**, **meanIoU** and **weightedIoU** were determined as **95.74**, **86.95** and **99.42**, respectively. **MeanBFScore** which is one of the most important metrics was resulted as **92.94**.

2.3 Proposed Solution

Considering the above mentioned existing approach, a Brain Tumor Prediction and Classification using ResNet50 is proposed which involves training a ResNet50 model on a labeled dataset of brain tumor images to classify them into different tumor types or categories. The approach employed to detect and classify Brain Tumor mainly consists of the following stages:

- Image Augmentation
- Transfer Learning using ResNet50 Model
- Web Application Integration

2.3.1 Image Augmentation

Image augmentation is a technique commonly used in deep learning for enhancing the training dataset by applying various transformations to the existing images. It helps to increase the diversity and variability of the training samples, thereby improving the model's ability to generalize and perform well on unseen data. In the context of brain tumor prediction using the ResNet50 model, image augmentation plays a crucial role in mitigating overfitting, handling class imbalance, and improving the model's performance.

Figure 2.3 represents various image augmentation techniques that can be applied to brain tumor images, some of which include:

- **Rotation**: The images can be rotated by a certain degree to simulate different orientations. This helps the model to be invariant to the rotation of tumors in the brain.
- **Horizontal and Vertical Flipping**: Flipping the images horizontally or vertically provides additional training samples and helps the model learn features from different perspectives.
- **Zooming**: Randomly zooming into or out of the images can simulate different scales and focal lengths, making the model more robust to variations in tumor size.
- **Shearing**: Applying a shearing transformation introduces slant or skewness to the images, mimicking potential distortions in real-life brain tumor images.

- **Shifts**: Shifting the images horizontally or vertically adds variations in the position of the tumor within the image, making the model more invariant to the position of the tumor.

- **Gaussian Noise**: Adding random Gaussian noise to the images helps the model become more robust to noise and variations in imaging conditions.

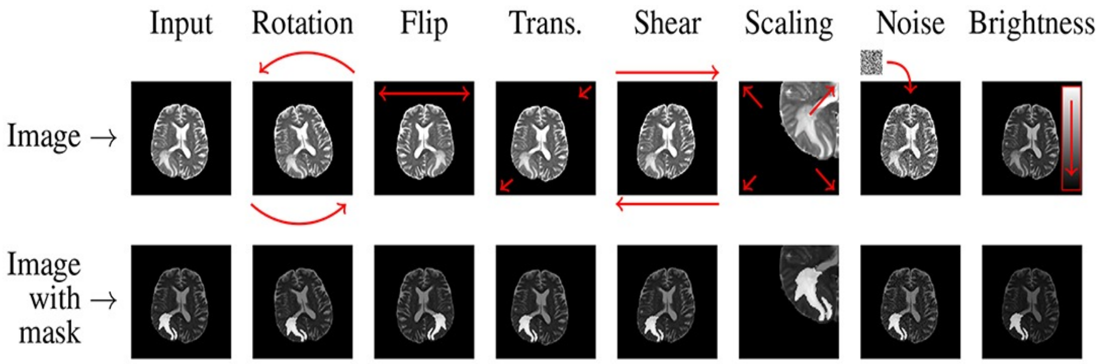


Figure 2.3: Image Augmentation Techniques

By applying these Image Augmentation techniques, a larger and more diverse dataset can be generated, which improves the model's ability to generalize and make accurate predictions on unseen brain tumor images. Image augmentation is especially useful when the available training dataset is limited, as it helps overcome the problem of insufficient data by generating synthetic variations.

2.3.2 Transfer Learning (ResNet50)

Transfer learning is a powerful technique in deep learning that involves leveraging pre-trained models on large-scale datasets to solve new tasks with smaller datasets.

In the context of brain tumor prediction using the ResNet50 model, transfer learning plays a crucial role in achieving accurate and efficient predictions. ResNet50, as shown in Figure 2.4, is a Deep Convolutional Neural Network (CNN) model that has been pre-trained on a large dataset (e.g., ImageNet) containing millions of images. It has learned to extract and represent high-level features from images, making it a valuable asset for tasks like brain tumor prediction.

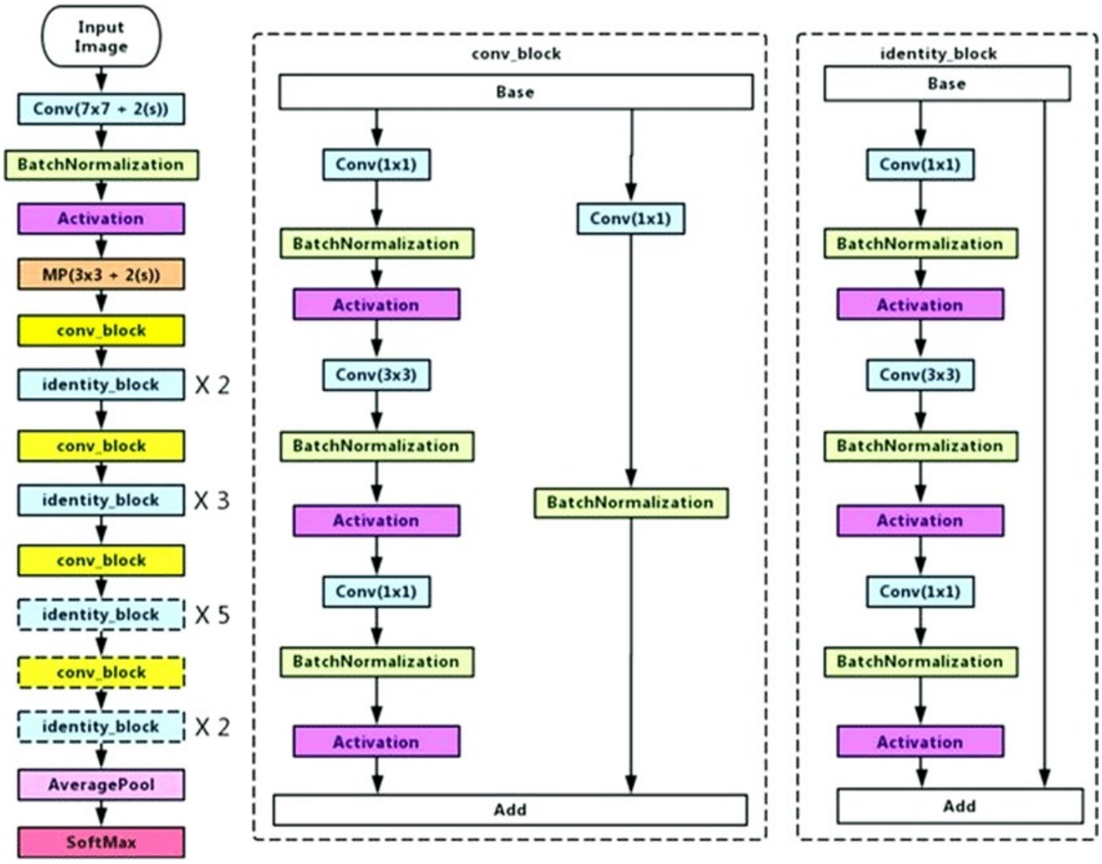


Figure 2.4: ResNet50 Model

Transfer learning in brain tumor prediction using the ResNet50 model typically involves two steps:

- **Pre - trained Model Initialization**: The pre-trained ResNet50 model is loaded, and its weights and architecture are imported. These weights capture general features from the large-scale dataset on which the model was trained, such as edges, textures, and shapes. By using a pre-trained model, one can benefit from the knowledge and feature representations learned from a diverse range of images.

- **Fine - tuning and Customization**: In this step, the pre-trained ResNet50 model is adapted and fine-tuned to the specific task of brain tumor prediction. The last few layers of the model, known as the ”top” layers, are replaced or modified to match the number of classes in the brain tumor dataset. These top layers are responsible for making the final predictions. By training only these top layers while keeping the lower layers frozen, overfitting can be prevented and retain the general features learned by the model can be retained.

Using transfer learning with the ResNet50 model gives several benefits such as, Improved

Performance, Efficient Training and Addressing Data Scarcity. It enables accurate predictions, efficient training, and better utilization of limited data resources.

2.3.3 Integration with Web Application

Integration with a web application refers to the process of incorporating a machine learning model, such as a brain tumor prediction model, into a web-based application. It involves combining the functionality and capabilities of the model with the user interface and interactivity provided by the web app. It has many advantages such as, User-friendly Interface, Accessibility, Remote Access, Real-time Predictions, Data Visualization, etc.

After training our deep learning model, it learnt to make accurate predictions by adjusting its internal parameters based on the input data. Once the training process was completed and the model had achieved satisfactory performance, it was saved to an .h5 file (Hierarchical Data Format 5 (HDF5) format file) for future use. By saving the model to an .h5 file, the trained model was easily loaded and reused later without having to retrain it from scratch. Later, this file was used in Flask framework along with the frontend integration (Web Application) and the results were predicted accordingly.

2.4 System Requirements

The project's system requirements are listed below :

- **Processor**: 11^{th} Gen Intel® Core (TM) i5-1145G7 @ 2.60GHz 2.61

- **Architecture**: 64-bit, x64-based Processor

- **Memory**: 8 GB RAM

- **Chipset**: Intel

Chapter 3

LITERATURE SURVEY

3.1 Related Works

The Literature Survey for Brain Tumor Prediction using Deep Learning includes the following works:

X.Fu et al. [5] put forward and recommended a CNN for the segmentation of microscopic pictures (tissues and cells). The network consists of eleven consecutive normalization layers that have been convolutionally corrected. With a Dice Similarity Coefficient (DSC) of 0.947, it outperformed cutting-edge CNNs on cardiac histology image dataset (labeled fibrosis, background and myocytes). It can also be smoothly trained from beginning to end and keeps image resolution while capturing fine-grained information. The learning data should include traits from the entire image collection, traits from each class, and color variations in specific structures for optimal results.

W.Zhang et al. [6] came forward with deep CNNs, as shown in Figure 3.1, to separate isointense stage brain tissues (baby brain tissues) into white matter (WM), grey matter (GM), and cerebrospinal fluid (CSF), employing multi-modality Magnetic Resonance images, which is crucial for understanding early brain development in both health and disease. Results revealed that, when it came to segmenting baby brain tissues, CNN outperformed earlier techniques. The inquiry about appeared that CNN seems to offer more exact and quantitative computer modeling and comes about for the division of infant tissue pictures. In this paper a few slices (2D images) were segmented manually and if labeled data were available, CNN can be used for 3D image segmentation.

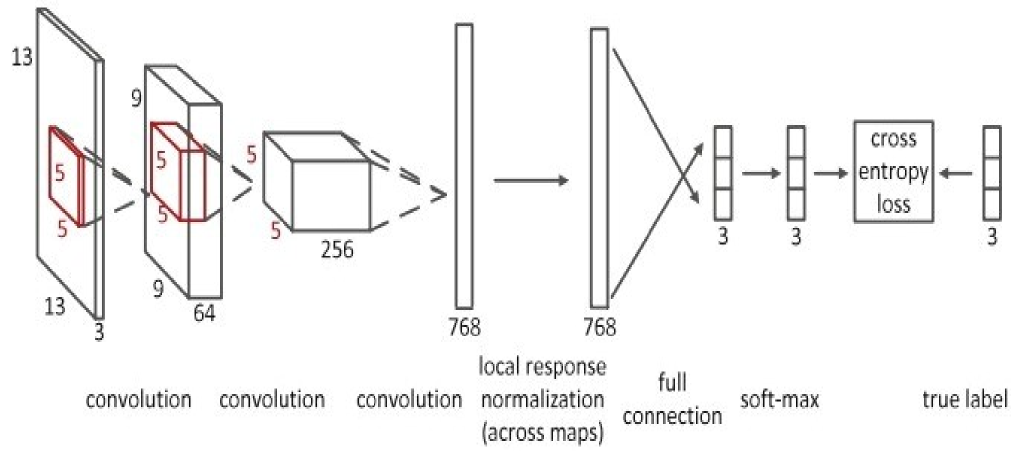


Figure 3.1: [6] Architecture of CNN taking patches of size 13 x 13 as inputs.

P.Mlynarski et al. [7] suggested a CNN model that integrates the advantages of the long-range 2D and the short-range 3D context. The imposed architectural model solves the issues of the missing MR images in the course of training period. A hierarchical decision model is used to aggregate the results of different segmentation models in order to get beyond the restrictions of certain neural network architectural choices. Finally, a quick and effective training algorithm for big CNN models is shown. This technique yields accurate Dice Scores of segmentation of total tumor, tumor core, enhancing core are 0.918, 0.833, 0.854 respectively.

S.Maharjana et al. [8] pointed to enhance the classification exactness by diminishing the hazard of overfitting issues, supporting multi-class classification, and centering on the classification exactness of the diverse sorts of tumors from the 3D MRI pictures. The proposed framework comprises of CNN with an altered softmax loss func. and regularization. The proposed arrangement is superior compared to the other classification strategies based on a likelihood score and exactness higher than 2% of the named information and an execution time of 40–50 milliseconds less. This paper tackles the issues of two-fold (binary) classification, preparing time, and overfitting of the information.

S. Alqazzaz et al. [15] applied a FCNN SegNet on 3D datasets for 4 MRI modalities. This algorithm for precisely segmenting a brain tumor attempts to locate the complete tumor volume and divide it into four sub-tumor regions. The proposed approach consists of four basic steps: (i) Data pre-processing; (ii) SegNet network-based image segmentation of brain tumors; (iii) Post-processing; (iv) SegNet_Max_DT. To evaluate the suggested approach, the Brain Tumor Segmentation 2017 (BraTS 2017) dataset is utilized. The presented algorithm was put into practice using MATLAB 2018a, and the segmentation outcomes were quantitatively assessed using the F-measure (evaluation metric). The outcomes show that this suggested methodology is capable of totally segmenting the tumor and sub-tumor regions automatically.

Li Sun et al. [16] has given an approach in which the brain tumor detection and survival prediction is finished primarily with the assistance of deep learning - based frameworks, shown in Figure 3.2. BraTS 2018 dataset was utilized to implement segmentation and survival prediction. so as to boost up the performance and scale back the bias within the result. Tumor segmentation was done with the help of 3 totally different three-dimensional CNN architectures by a principle called, voting. So as to get potent options, a DTs (Decision Tree) model of regression was used with gradient boosting for the variance reduction. To pick the best range of strong options Cross Validation was applied. The survival of patients was expected by training the Random Decision Forest model. Results of Survival Prediction were sixty one percent correct and classified the survivors as short-term, mid-term and long-term survivors. The obtained results were analyzed and a conclusion was drawn that the single models have weaker performance when compared to collective models.

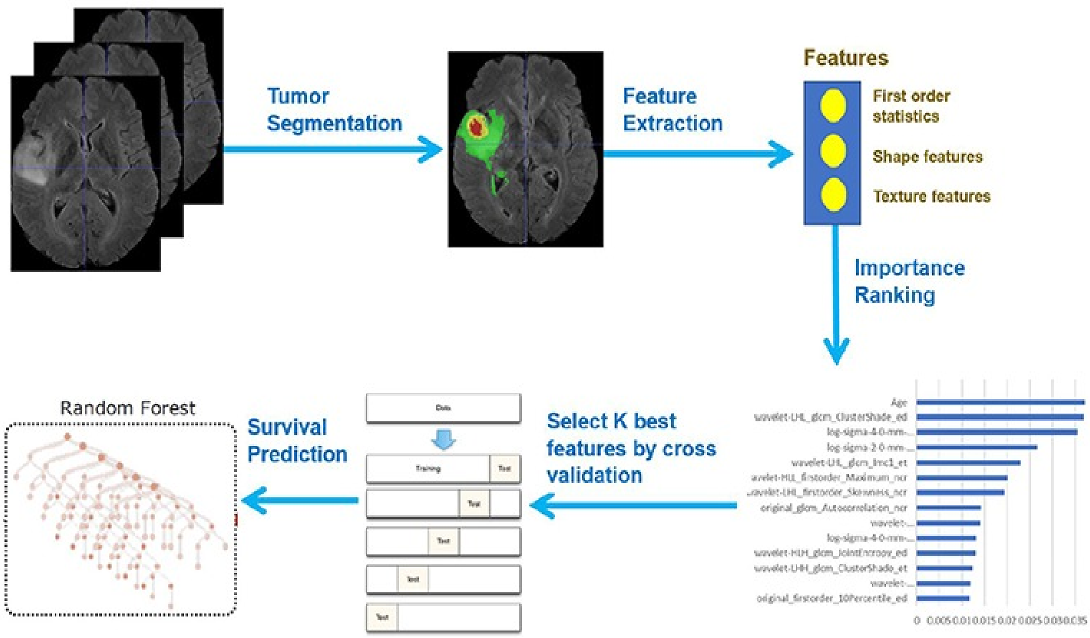


Figure 3.2: [16] Framework Overview using Multi-Modal MRI Scans.

U. Baid et al [17] has given an approach in which the 3D U-Net design was accustomed to segment numerous radiologically specifiable sub-regions like lump, enhancing tumor, and sphacelus. This design has been enforced using Tensorflow library. The DCNN-primarily based design was accustomed for capturing the context (contracting path) and to observe the precise localization of the tumor. To train the 3D U-Net design, 3D patch extraction was done from Brain Tumor Segmentation dataset (training).The results of this approach show the importance and use of patch-dependent 3Dimensional U-Net for segmenting tumor accurately. This study shows that weighted patch-based segmentation approach is healthier in terms of performance in comparison to the pixel-based approach.

D.Ataloglou et al. [18] formulated a completely programmed division framework as shown in Figure 3.3, with incredible exactness and fast comes about with the help of Deep Learning procedures. A CNN is used in the suggested paper, along with specific segmentation and error correction processes. By merging numerous datasets through transfer learning, they investigated various training methodologies utilizing CNN-based segmentation, which enhances segmentation quality. Utilizing two isolated open datasets, the proposed strategy was assessed and compared favorably to the existing strategies. A mean Dice value of 0.9015 was obtained in the EADC-ADNI HarP dataset when comparing the output of the approach with the ground truth manual tracings, whereas 14.8 seconds were needed to segment a whole MRI volume.

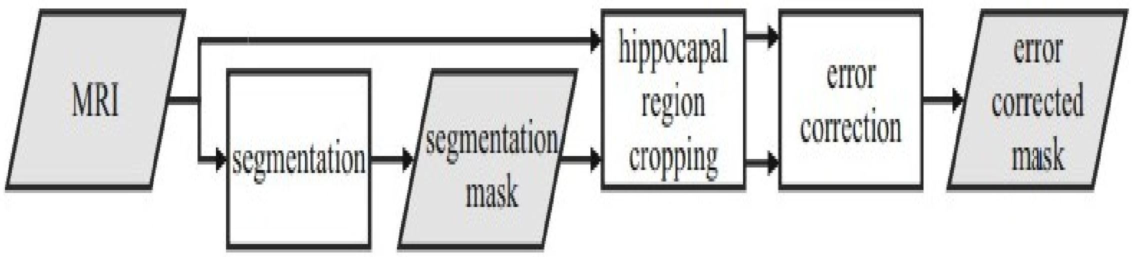


Figure 3.3: [18] Top Level Architecture of the Proposed Method

G. Jimenez et al. [21] introduced 2 deep learning architectures to proficiently find and classify the cell division in an exceedingly histopathological tissue sample. The datasets utilized for this include those employed in the ICPR-2012 contest. The primary technique has 2 elements, involving a pre-processing of the histopathological tissue image and a

CNN used for classification (binary). The projected technique achieved accuracy of 95 percent in testing, the F1-score being 94.35 percent. The second approach involves the employment of semantic segmentation. The projected technique achieved an accuracy of 95 percent. Some methodologies specifically, Alex-Net and U-Net were adapted to compare and verify its relevance in segmentation and classification. The results show that the performance of DL (deep learning) approaches tends to improve the accuracy by nearly 7 percent. The U-Net approach is taken into account and is found to be more precise than the Alex-Net approach.

R.Martins et al. [22] explored the issue of multi-modal segmentation of image, and have proposed an innovative metric to influence the contour and global accuracy. The proposed metric is evaluated. In this paper, the issue of discovering one accurate system of measurement that is intended for global-classification of pixels and better segmentation of contour is addressed. Also a new system of measurement is proposed with the help of Jaccard index. The new metric introduced in this paper for supervised segmentation is found to calculate the quality and value of the segmented regions along with their boundaries. The proposed system of measurement includes the rate of suitably labeled pixels & helps in achieving better results for semantic segmentation.

A.Erdamar et al. [24] presented a deep learning based method called CNN in order to classify the single cell electrophoresis images. This technique was used to demonstrate the usefulness of DL Algorithm on the images of cells. In this, the CNN which has been used is tested and trained with huge accuracy. Results obtained demonstrate that the CNN Network Algorithm was used to categorize 5 diverse scores of single-cell electrophoresis images successfully. This analysis algorithm used for images in this study was evaluated by MATLAB(R). The CNN algorithm used in this work has shown the results like high sensitivity, specificity, and accuracy. This study shows that CNN can quantitatively regulate the comet assay scores. The images used consist of five different scores.

Z. Liu et al [25] introduced a consistent architecture represented in Figure 3.4, with the aim to speed up the working of both 3D and 2D CNNs. The convolutions have been mapped to matrix multiplications here. With the intent of computing the matrix multiplications, a 2-Dimensional MAC [Multiply and Accumulate] array is utilized. An image (accelerator) with High Level Synthesis enforced and this accelerator was tested on 3 of the

CNN models namely: Alex-Net, 16 layerVGGnet, and 3D graphics technique called C3D. A cost-effective matrix mapping module is projected so as to avoid information replication throughout the convolutional windows. Tentative results obtained show that, the accelerator achieves progressive output performance on each 2-dimensional and 3-dimensional CNNs, with a lot of improved energy effectiveness when compared with the C.P.U. and GPU. This paper concludes that the design introduced fully utilizes the resources for computation and states that this explicit application can be often used with ASIC implementations.

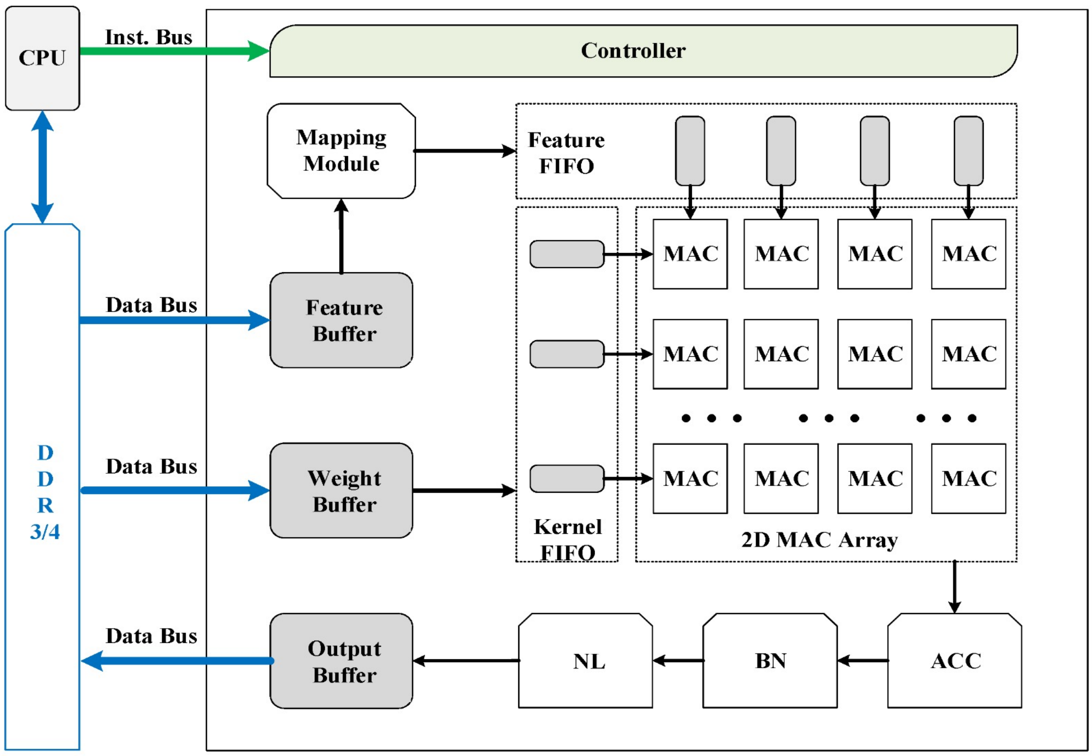


Figure 3.4: [25] Uniform Accelerator Architecture for 2D and 3D CNNs.

Based on an extensive literature survey, the conclusion drawn is that fully automated segmentation techniques are prioritized for brain tumor detection, with manual and semi-automated techniques having significant drawbacks. Among the various automated techniques explored, the CNN algorithm demonstrates the highest accuracy and precision rate. Given these findings, the **ResNet50 Model** (a CNN-based transfer learning approach) has been chosen for implementing Brain Tumor Prediction and Classification. The implementation categorizes tumors into four distinct types: Meningioma, Pituitary, Glioma and No tumor. To facilitate user interaction and accessibility, the implemented model can be integrated into a web application using Flask, HTML, CSS, and JavaScript.

Chapter 4

ARCHITECTURE AND SYSTEM DESIGN

The overview of the system is depicted in Figure 4.1, and the following is a description of each stage:

(1) **Data Collection and Preparation**: A dataset of brain tumor MR images with appropriate labelling indicating the tumor type is gathered. This dataset was obtained as a reference from Kaggle (Brain Tumor MRI Dataset) along with real time data.

(2) **Data Pre-Processing**: Pre-processing entails scaling the photos to a constant resolution, normalizing pixel intensities, and augmenting the data if required to standardize the input data and enhance model performance. In order to increase the size of the dataset and enhance model generalization, augmentation techniques may be used, such as random rotations, flips, and zooms. If the dataset contains corrupted scans or missing data or noise, then Data Cleaning is performed to guarantee the quality and integrity of the data. After applying these image enhancing techniques, the dataset is split into three subsets: training, validation, and testing. The training set is used to train the deep learning model, the validation set is used for hyperparameter tuning and model selection, and the testing set is used for evaluating the final model's performance.

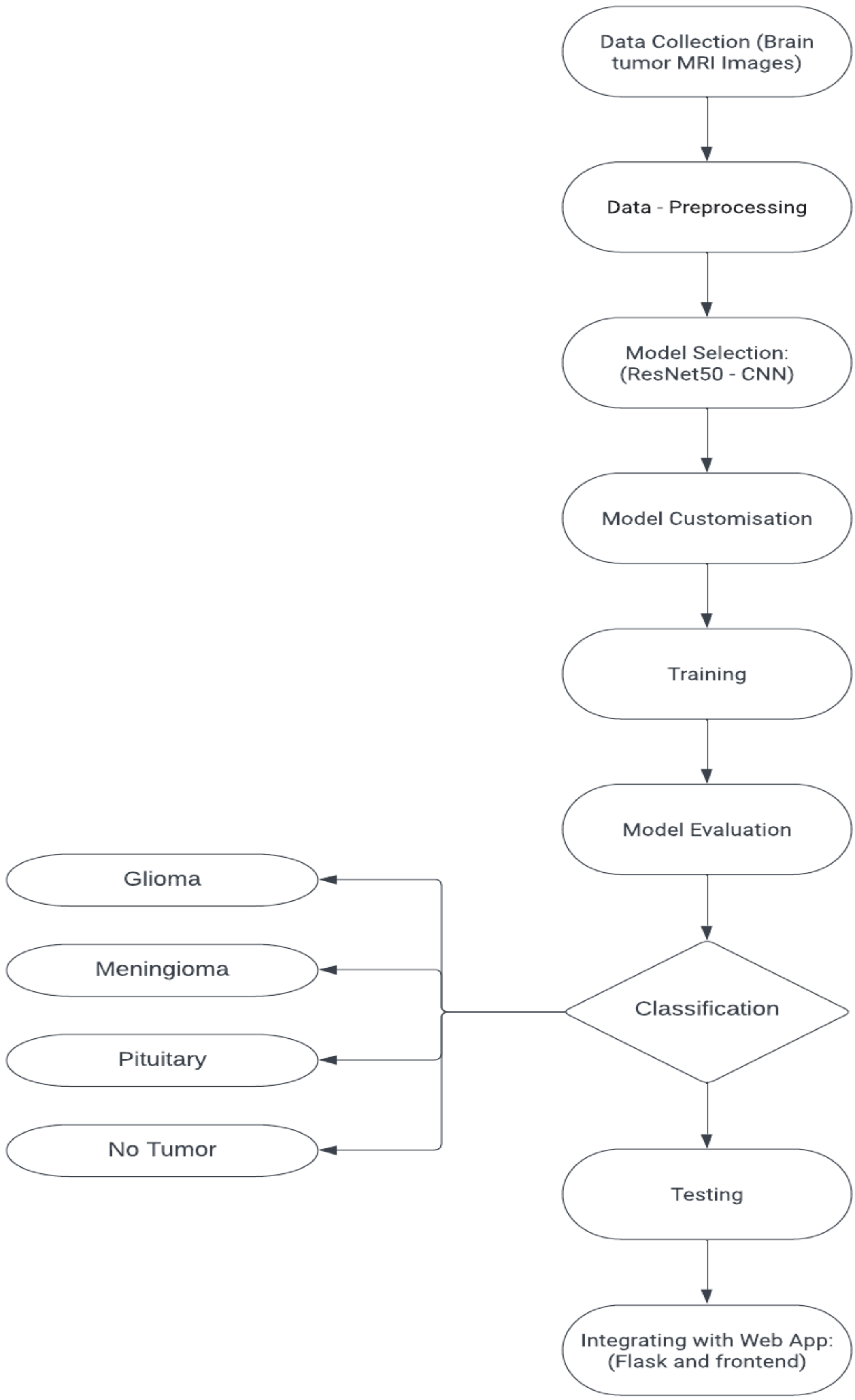


Figure 4.1: System Design / Flow Chart

(3) **Model Selection**: Here, ResNet50 architecture acts as the backbone model for brain tumor classification. ResNet50 is a deep convolutional neural network architecture that has already been pre-trained on a large dataset (e.g., ImageNet) containing millions of images. This model is chosen for the project since it showcased excellent performance in image classification tasks.

(4) **Model Customization**: Since the ResNet50 model is pre-trained on a large image dataset (e.g., ImageNet), transfer learning is used to fine-tune the model for brain tumor classification. The original classification layer from the ResNet50 is eliminated, and a new fully connected layer is added in its stead that corresponds to the number of tumor classes in the dataset.

(5) **Training**: The ResNet50 model is trained utilizing the labeled brain tumor dataset. The model gains the ability to extract features from the images and generate predictions based on the labels for the different tumour types throughout training. A suitable loss function, **categorical cross - entropy** is used which calculates the cross-entropy loss between the predicted class probabilities and the true class labels, and is frequently employed for multi - class classification problems. An optimization algorithm, **Adaptive Moment Estimation (Adam)** is used, which combines the benefits of both RMSprop and momentum methods. It adapts the learning rate for each parameter based on the estimate of the first and second moments of the gradients. These two are used to update the model's parameters.

(6) **Model Evaluation**: The trained model is evaluated using the validation set to assess its performance. The Performance Metrics such as accuracy, precision, sensitivity, F1 score and AUC are calculated to measure the model's classification performance.

(7) **Classification**: The tumor is classified into one of the 4 categories namely, **Glioma**, **Meningioma**, **Pituitary** and **No Tumor**.

(8) **Testing**: Once the model is trained and evaluated, the independent testing set was used to assess its performance on unseen data. The relevant metrics were computed to gauge the model's generalization ability and effectiveness in classifying brain tumors.

(9) **Integrating with Web Application**: This Brain Tumor Prediction and Classification Model is then incorporated into a web-based application to make it user-friendly.

Chapter 5

IMPLEMENTATION

5.1 Implementation Platform

5.1.1 Hardware

- **Processor**: 11^{th} Gen Intel® Core (TM) i5-1145G7 @ 2.60GHz 2.61
- **Architecture**: 64-bit, x64-based Processor
- **Memory**: 8 GB RAM
- **Chipset**: Intel

5.1.2 Software

- **Operating System**: Windows 11
- **Integrated Development Environment**: Visual Studio Code (VS Code)
- **Programming Language**: Python 3, HTML, CSS, Javascript, Flask
- **Tools**: GitHub

5.2 Implementation Details

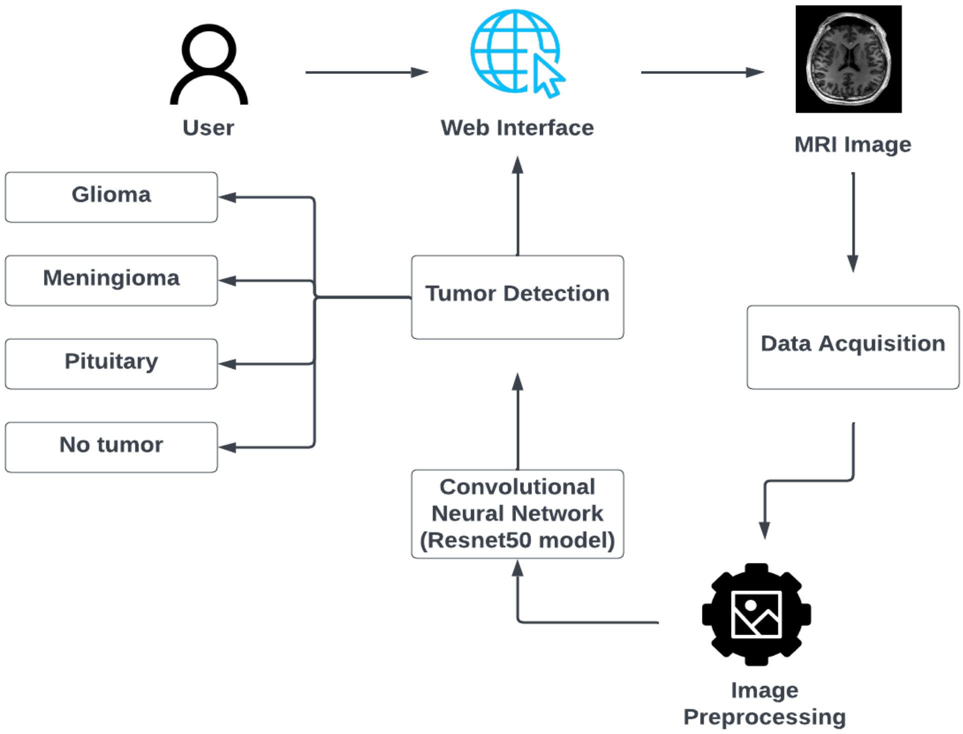


Figure 5.1: Architecture of the Proposed Solution

The Architecture of the proposed system is depicted in Figure 5.1. Initially, the dataset was acquired from Kaggle which consisted of brain MR images. The necessary libraries, such as Keras, Tensorflow, Matplotlib, Numpy, Imutils, etc. were imported to proceed with the further implementation.

Immediately after importing all the required libraries, the Pre-Processing stage as shown in the Figure 5.2 was carried out, including: data cleaning, resizing the images, etc. The labels were assigned for all the four categories of tumor. A threshold was set to the images, and based on that, a series of **Erosion and Dilations** were performed in order to remove any small regions of noise. The contours were found in threshold image, and then the largest among them was picked. The extreme points of the largest contour were found on the image with the help of array slicing and indexing operations and were cropped out. The dataset was split into **Training (80%)** and **Testing (20%)**.

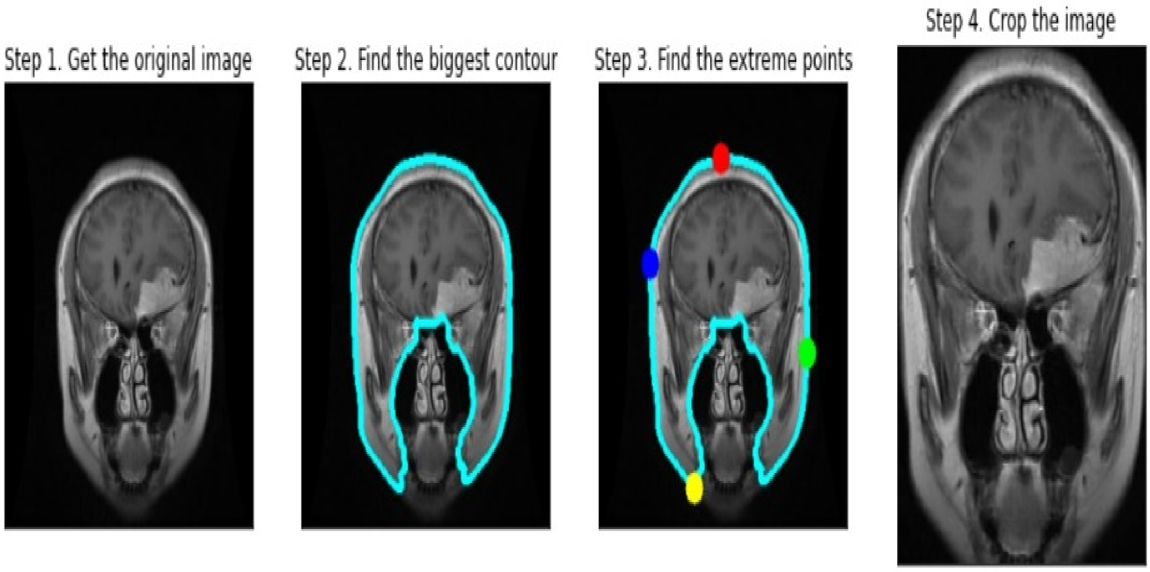


Figure 5.2: Pre-Processing stage

In Convolutional Neural Networks (CNNs), **Flattening** refers to reshaping the 2D image representation into a 1D vector before passing it to fully connected layers. This flattening operation is performed to transform the spatially structured image data into a format that can be fed into traditional fully connected layers commonly used in neural networks. Overall, flattening in CNNs allows for compatibility with fully connected layers, efficient parameter usage, and effective feature extraction, ultimately contributing to the network's ability to learn and make predictions on image data. Hence, flattening is performed on the brain MR images.

One-hot Encoding is done which is a technique used to convert categorical variables into a binary matrix representation. It creates a binary vector for each label where all elements are zero except for the index corresponding to the label, which is set to one. This representation is often required when training models that expect the target variable to be in a one-hot encoded format.

Image augmentation is carried out to mitigate overfitting and to improve the model's performance. It is a commonly used technique in deep learning for enhancing the training dataset by applying various transformations to the existing images. It helps to increase the diversity and variability of the training samples, thereby improving the model's ability to generalize and perform well on unseen data. Here, the original MRI scan as shown in Figure 5.3 is augmented using the parameters such as rotation, width-shift, height-shift, rescaling, zooming, brightness, horizontal and vertical flip. The resulting augmented images are presented in Figure 5.4.

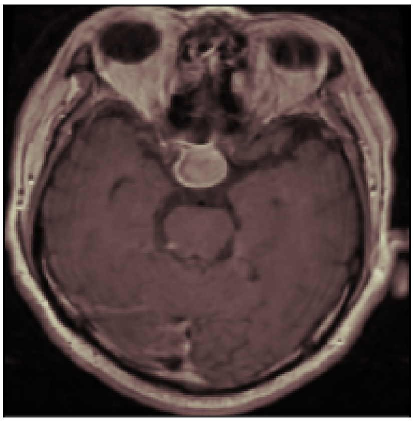


Figure 5.3: Original MR Image

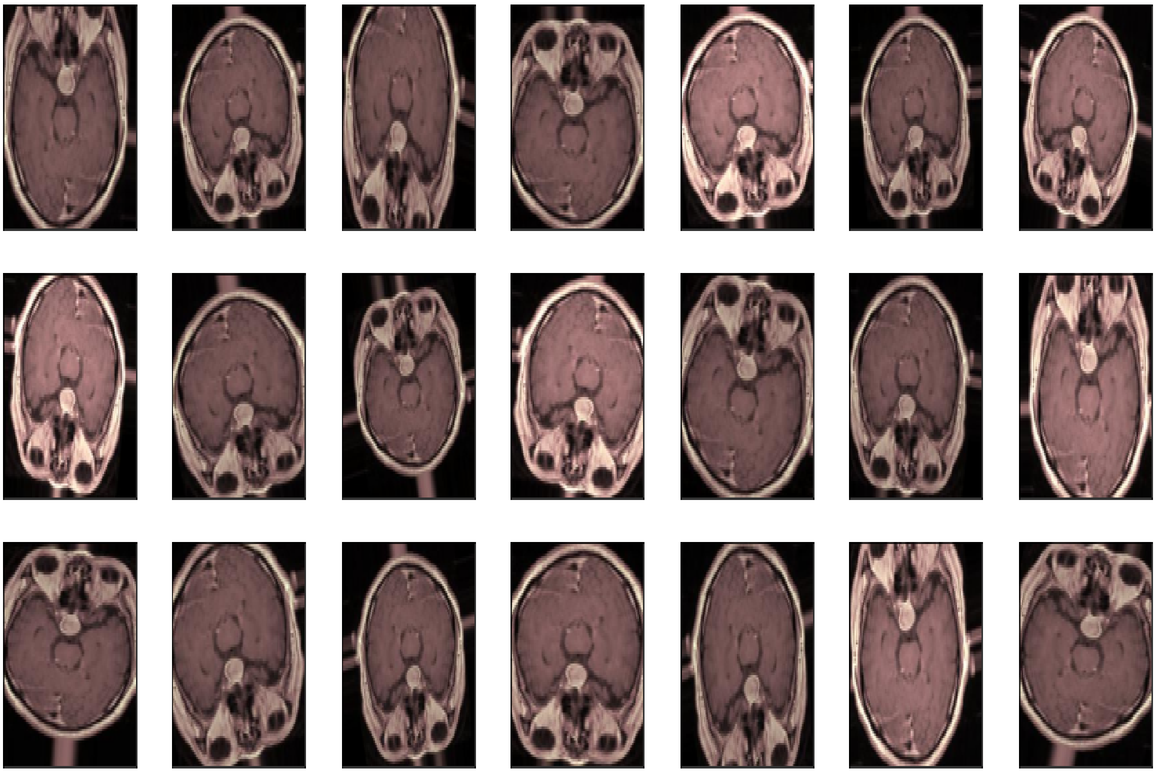


Figure 5.4: Augmented Images

Now, the ResNet50 model is loaded which is a Transfer Learning Technique, where the model is pre-trained but here, the outer layers have been replaced with **GlobalAverage-**

Pooling2D, **Dropout** and **Dense** layers. A suitable optimization algorithm (**Adam**) and an appropriate loss function (e.g., **Categorical Cross-Entropy**) are used for the classification task. The trained model is saved to **.h5 file** (**Hierarchical Data Format 5 (HDF5)** format file) for further implementation. The confusion matrix and ROC Curves are plotted.

By saving the model to .h5 file, the trained model was easily loaded and reused later without having to retrain it from scratch. Later, this file was used in Flask framework along with the frontend integration (Web Application) as shown in Figure 5.5 and the results were predicted accordingly.

Integrating H5 model (typically a model exported from a deep learning framework like TensorFlow) with Flask in a web application is initiated by loading the H5 model file into your Flask application. This can be done using the appropriate libraries or frameworks for your chosen deep learning framework (e.g., TensorFlow, Keras). Depending on the requirements of our model, the model is passed for prediction. This can involve tasks like resizing, normalizing, or encoding the input data to match the expected input format of the model. Once the model is loaded and the input data is pre-processed, the model is used to make predictions. The appropriate routes and views were set up in the Flask application to handle incoming requests and return predictions as responses. Finally, the predictions were rendered.

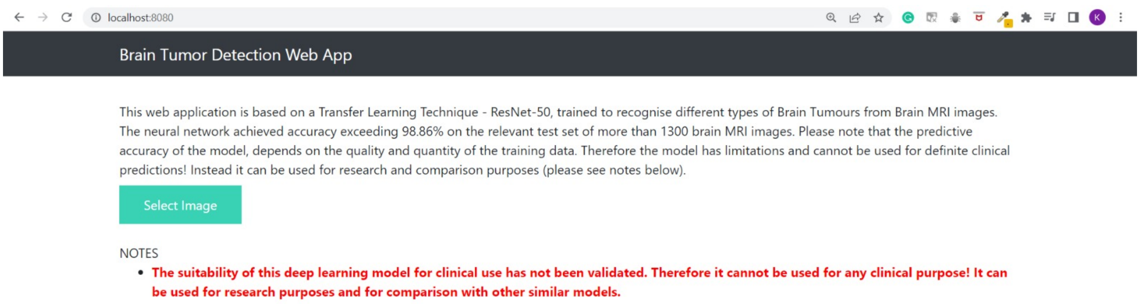


Figure 5.5: Display of the Web Application

5.3 UML Diagram

UML (Unified Modeling Language) Diagrams typically represent the structural aspects of a system and not the specific implementation details. The below Figure 5.5 is a simplified UML diagram for the Brain Tumor Prediction system:

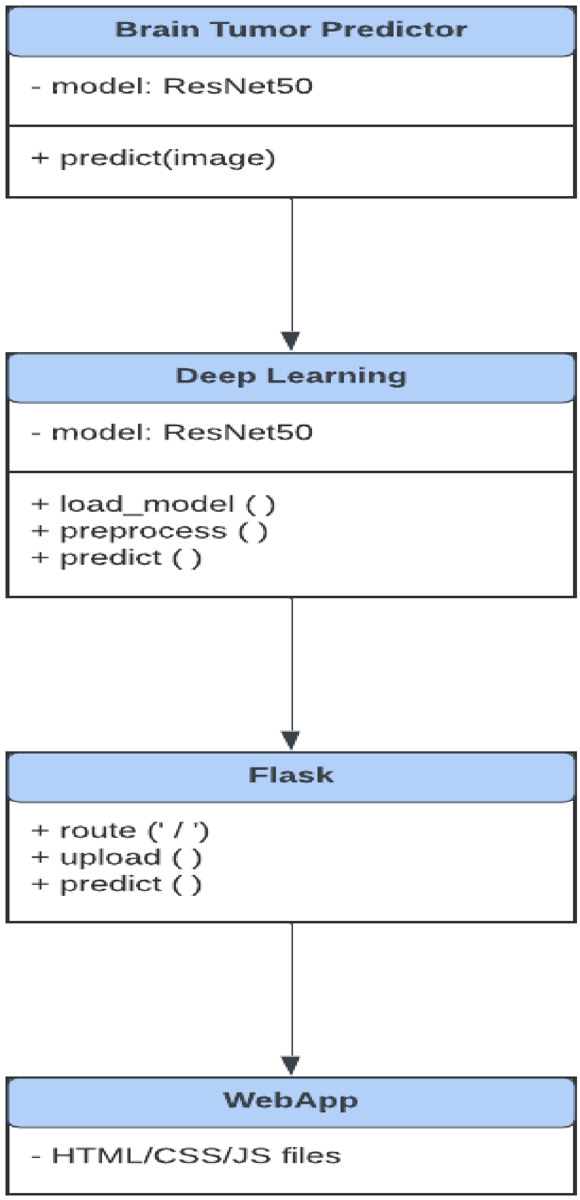


Figure 5.6: UML Class Diagram

BrainTumorPredictor: This class represents the main entry point for the brain tumor prediction system. It encapsulates the model object, which is an instance of the **ResNet50 Model** used for prediction. It exposes a predict method to make predictions on brain tumor MRI scans.

DeepLearning: This class is responsible for the Deep Learning aspects of the system. It contains the model object, which is an instance of the ResNet50 model. It provides methods such as **load_model ( )** to load the pre-trained model, **preprocess ( )** to preprocess the input image, and **predict ( )** to make predictions using the model.

Flask: This class represents the Flask Web Application framework. It handles the web app integration part and provides routes for different URLs. It includes methods such as **route (' / ')** to define the home page route and **upload ( )** and **predict ( )** to handle the image upload and prediction process.

WebApp: This class represents the web application part of the system. It consists of **HTML**, **CSS**, and **Javascript files** that define the user interface and interaction with the system.

5.4 Sequential Diagram

The Figure 5.6, depicts a sequential diagram illustrating the step-by-step flow of interactions between the **User**, **Web Application**, and **Deep Learning Model** during the Brain Tumor Prediction process. It highlights the major actions and information exchanges involved in the system, providing a clear overview of the process flow.

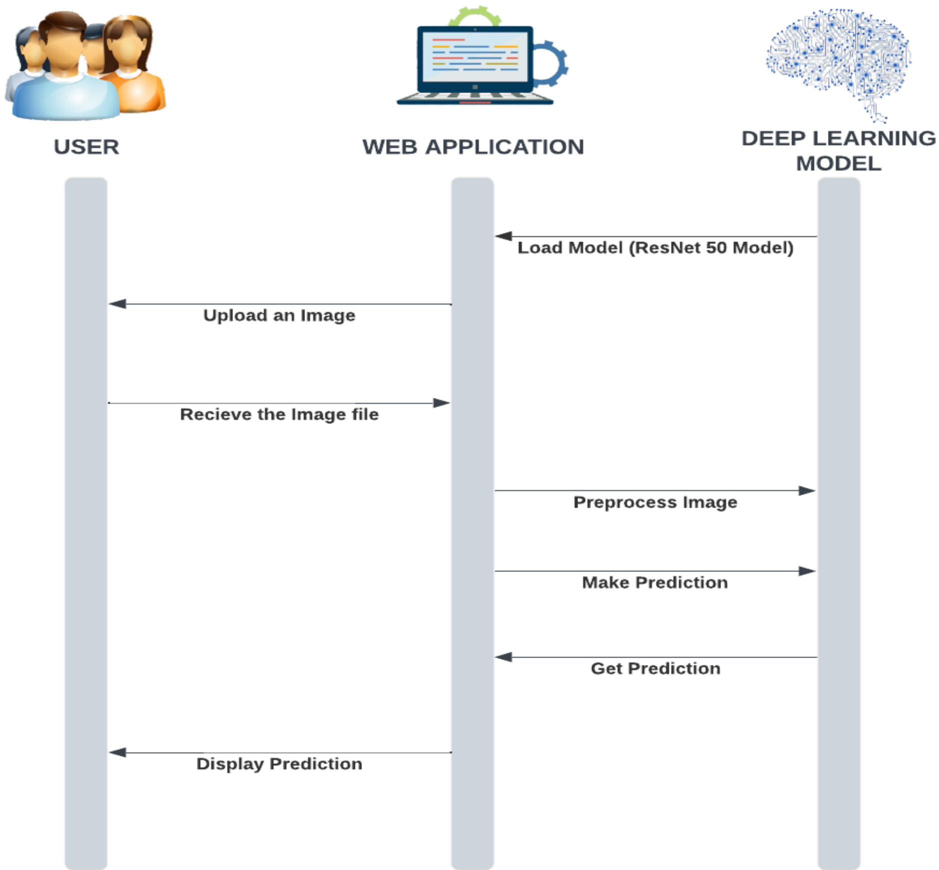


Figure 5.7: Sequential Diagram

(1) Initially, the Deep Learning model, **ResNet50 is loaded** to the Flask framework.

(2) The user initiates the process by interacting with the web application. They typically access a web page that provides an interface for uploading an image for brain tumor prediction.

(3) The user **uploads** an image by interacting with the web application.

(4) The web application **receives the image file** that was uploaded by the user.

(5) Once the image file is received, the web application sends the file to the deep learning model for further **Processing** and **Prediction**.

(6) The deep learning model (ResNet50 model), takes over the processing of the image. It preprocesses the image to ensure it is in the proper format and ready for prediction.

(7) The preprocessed image is passed to the ResNet50 model. The ResNet50 model, which has been pre-trained on a large dataset, performs the actual prediction on the image.

(8) The ResNet50 model generates the prediction result, classifying the brain tumor into one of the four categories: **Meningioma**, **Pituitary**, **Glioma** and **No Tumor**.

(9) The prediction result is returned from the deep learning model to the web application.

(10) The web application receives the prediction result from the deep learning model.

(11) The web application **displays the prediction result** to the user. This can be done by updating the existing page with the prediction information.

Chapter 6

TESTING

In order to test brain tumors from the MRI scans, a dataset of 1311 testing images was utilized. The dataset consisted of four different classes, namely: Glioma, Meningioma, Pituitary, and No Tumor/ Healthy. Each class has a varying number of testing images:

- Glioma - **300** images
- Meningioma - **306** images
- Pitutary - **300** images
- No Tumor - **405** images

To ensure effective evaluation, 8:2 split was implemented for training and testing the dataset. This means that 80% of the images were used for training the model, while the remaining 20% were reserved for testing the model's performance. This testing resulted in an accuracy of 98.86% of the deep learning models in classification of Brain Tumor from MRI scans.

During the testing phase of the brain tumor classification model, the MRI scan uploaded was successfully classified. As shown in Figure 6.1, the image uploaded for testing was **Glioma** tumor, and the model accurately predicted the tumor type as Glioma, aligning with the expected output based on the provided dataset and ground truth labels.

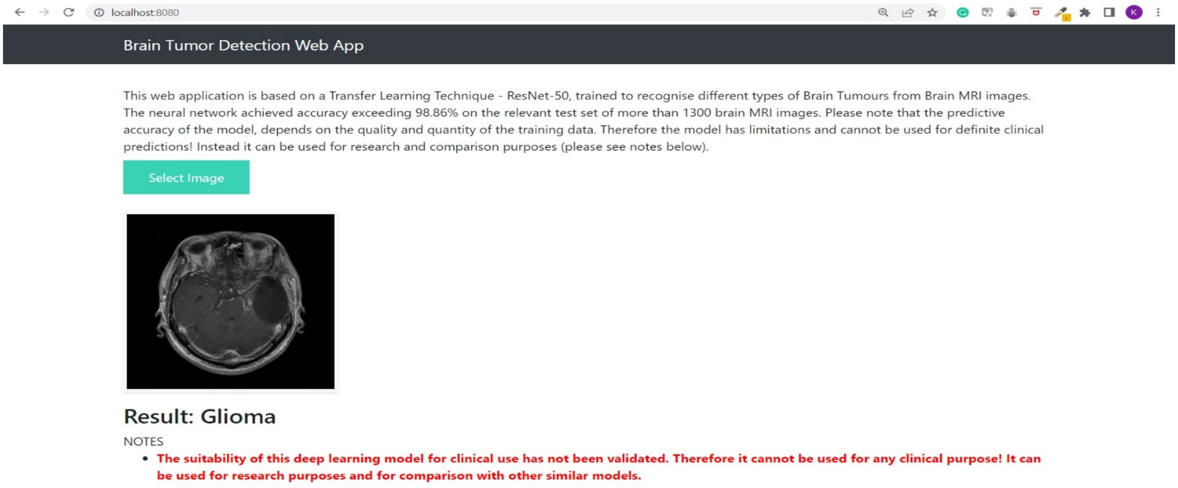


Figure 6.1: Correctly Classified Output (Glioma Tumor)

Similarly, the below figures i.e., Figure 6.2, Figure 6.3, Figure 6.4, shows the correctly classified tumors for **Meningioma**, **Pituitary** and **No Tumor** respectively.

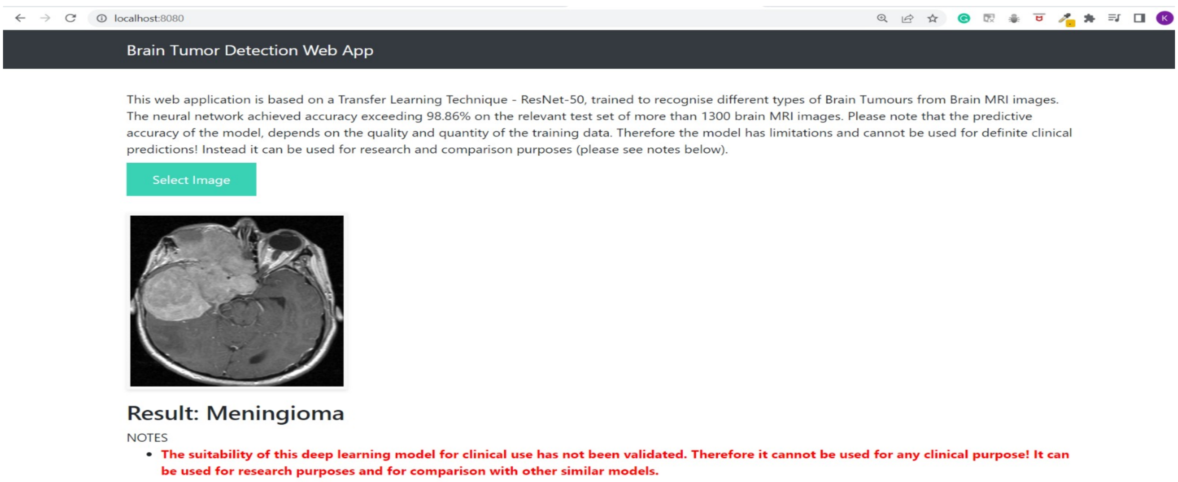


Figure 6.2: Correctly Classified Output (Meningioma Tumor)

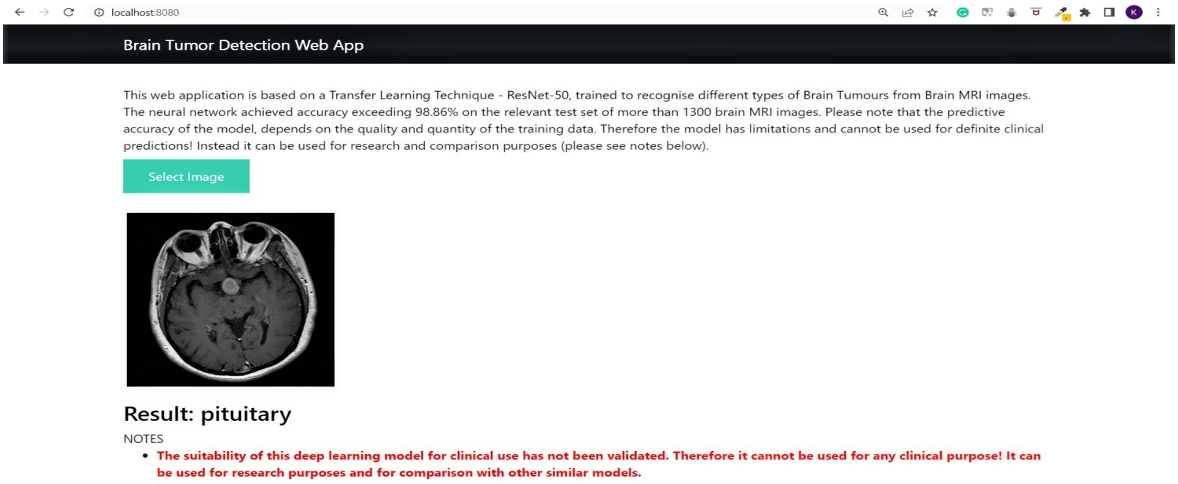


Figure 6.3: Correctly Classified Output (Pitutary Tumor)

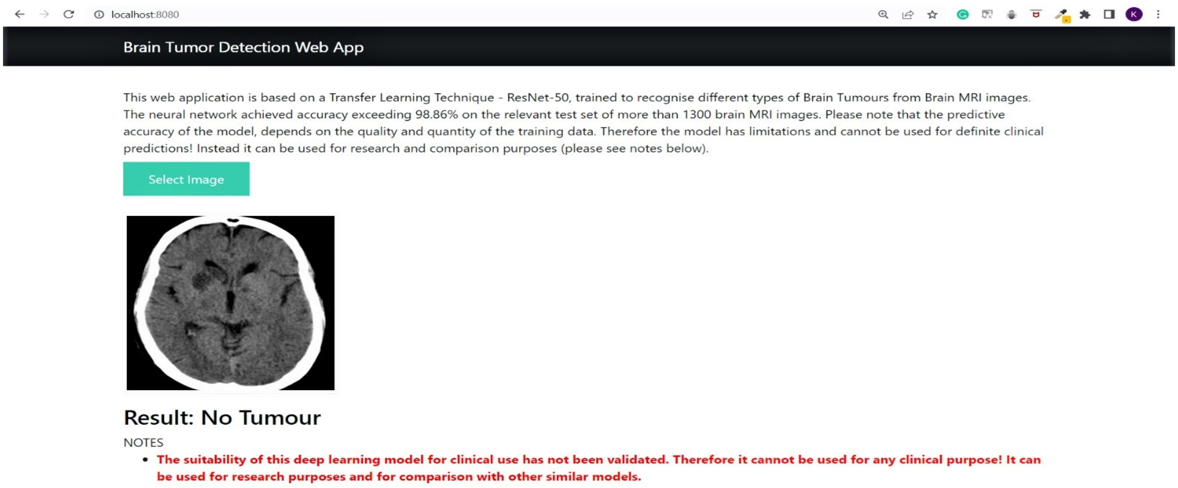


Figure 6.4: Correctly Classified Output (No Tumor)

A misclassified output encountered is shown in Figure 6.5 and Figure 6.6. The image uploaded for testing was **Meningioma** tumor, which was the expected output based on the provided dataset and ground truth labels. However, the model predicted the tumor type as **Pituitary**, indicating a misclassification.

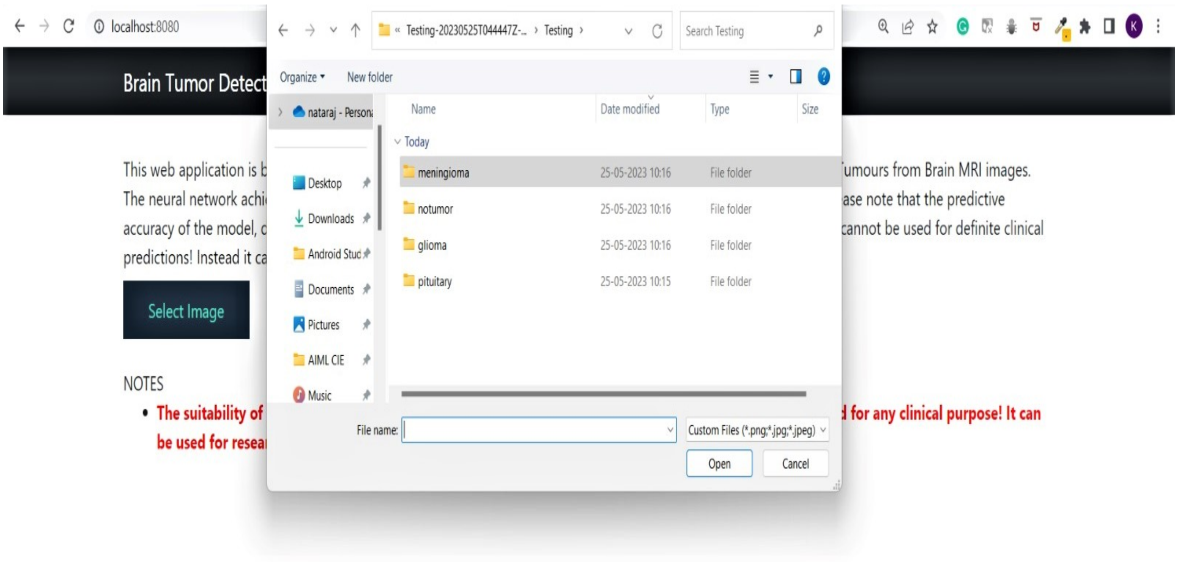


Figure 6.5: Uploading an MRI scan from Testing Dataset (Meningioma Tumor)

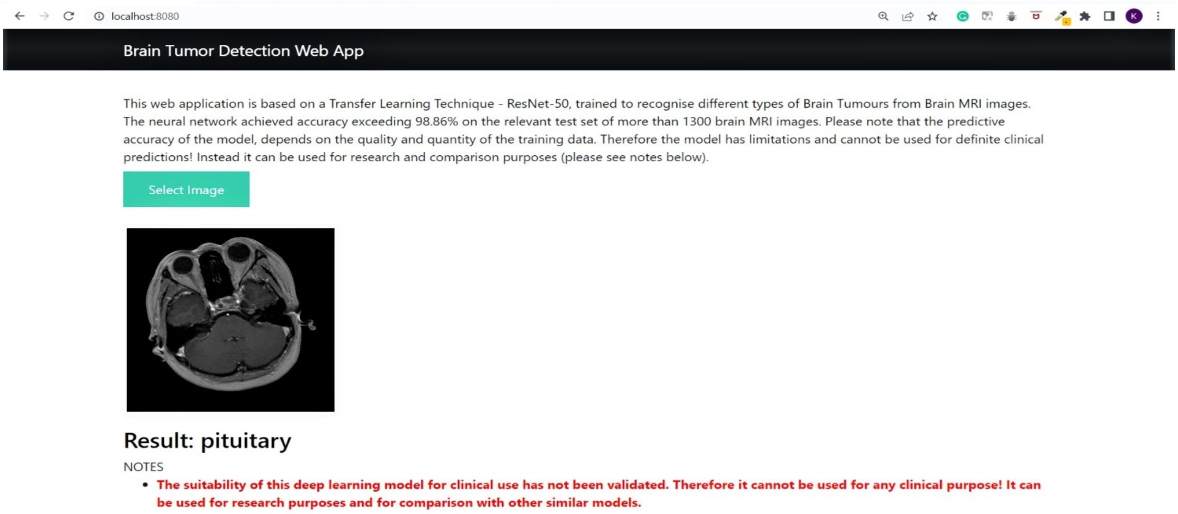


Figure 6.6: Misclassified Output (Pitutary Tumor)

By training the model on a diverse range of images from different tumor classes, it could learn to identify specific features and patterns associated with each type of tumor. The testing phase would then validate the model's performance, enabling the researchers and healthcare professionals to make informed decisions and provide effective treatment strategies for patients with brain tumors.

Chapter 7

RESULTS

The **ResNet50 Model** is designed to provide a classification output indicating the presence of a brain tumor (specifically Glioma, Meningioma, or Pituitary) in a given MRI image. However, it is important to consider various factors that can influence the accuracy and reliability of the results.

The quality and diversity of the training dataset play a crucial role in training an effective model. A well-curated dataset with a wide range of tumor types and variations can improve the model's performance. Additionally, proper pre-processing techniques are applied to enhance the quality of the input images. This pre-processing step helps to improve the model's ability to extract relevant features and make accurate predictions. Furthermore, fine-tuning of hyperparameters, such as learning rate and regularization, is performed to optimize the model's performance. Hyperparameter tuning aims to find the optimal configuration that balances the model's ability to generalize well to unseen data while avoiding overfitting or underfitting.

The training progress of the brain tumor prediction model was monitored by analyzing the **Accuracy Curves** and **Loss Curves**. The Accuracy Curve in the Figure 7.1, illustrates the progression of the model's accuracy over each epoch during training. It demonstrates how well the model is improving its ability to correctly classify brain tumor images. A higher accuracy value indicates that the model is becoming more proficient at distinguishing between different tumor types, leading to more reliable predictions.

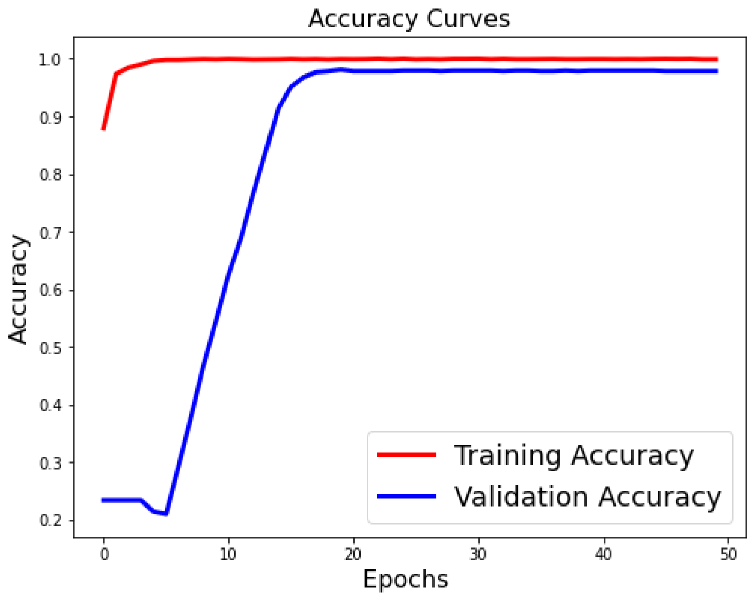


Figure 7.1: Accuracy Curves

The Loss Curve depicted in Figure 7.2, reveals the model's training and validation loss values across each epoch. The loss value represents the discrepancy between the predicted outputs of the model and the true labels. A decreasing loss value indicates that the model is converging towards optimal predictions as it minimizes the difference between predicted and actual values.

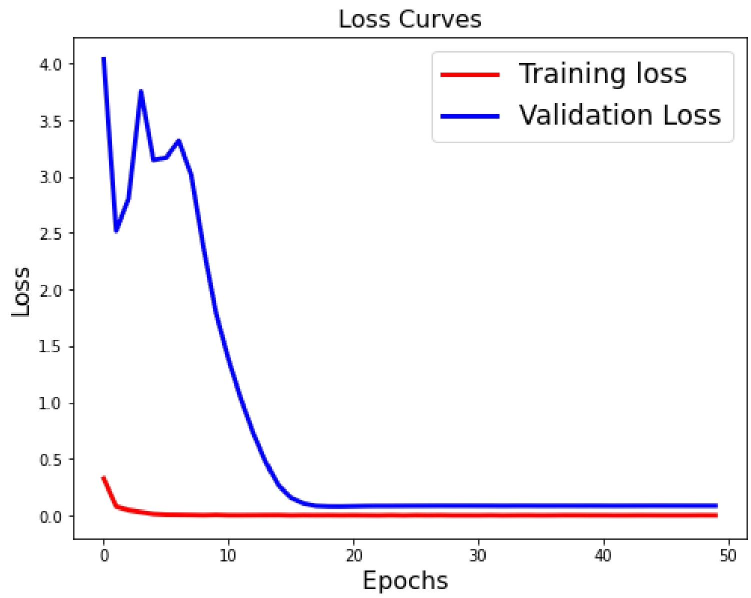


Figure 7.2: Loss Curves

To evaluate the performance of the model, rigorous testing is conducted using a separate dataset. The Evaluation Metrics andthe Confusion Matrix are displayed in Figure 7.3 and

Figure 7.4 respectively. The **Accuracy** of **98.78%** suggests that the ResNet50 model for brain tumor detection shows promising results. However, it is important to interpret this accuracy in conjunction with other evaluation metrics (Figure 6.1) to have a comprehensive understanding of the model's performance.

	precision	recall	f1-score	support
glioma	0.99	0.97	0.98	300
meningioma	0.97	0.99	0.98	306
no_tumor	1.00	1.00	1.00	405
pituitary	1.00	1.00	1.00	300
accuracy			0.99	1311
macro avg	0.99	0.99	0.99	1311
weighted avg	0.99	0.99	0.99	1311

Figure 7.3: Evaluation Metrics

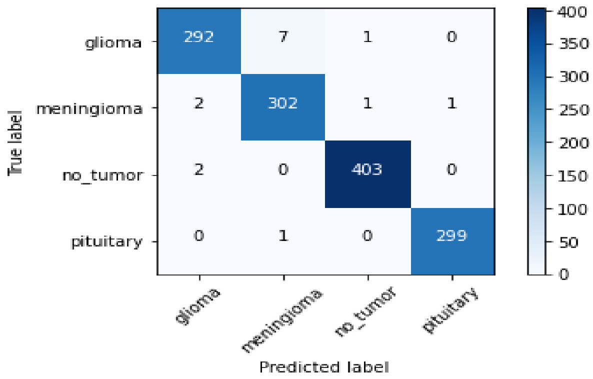


Figure 7.4: Confusion Matrix

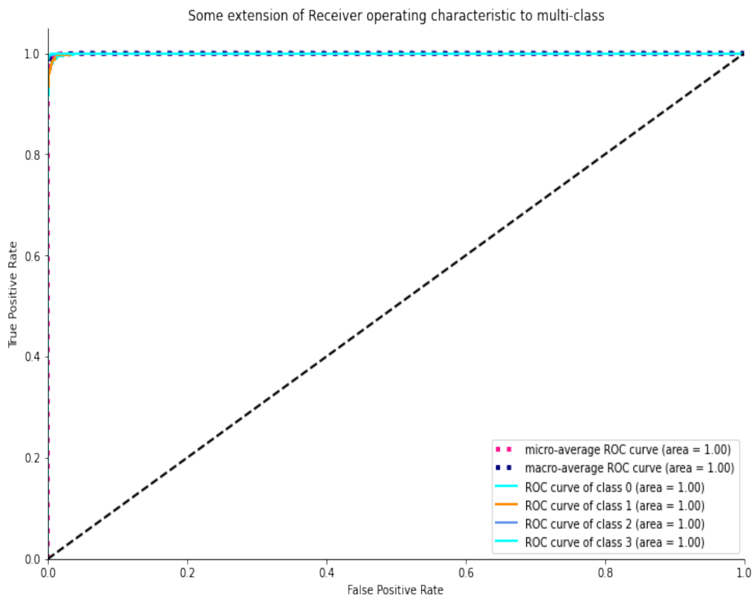


Figure 7.5: Receiver Operating Characteristic Curve

The **Precision** of **99.00%** indicates the proportion of correctly predicted tumor cases among all predicted tumor cases. **Sensitivity**, also known as **Recall**, provides an insight into the model's ability to correctly identify each tumor type. The sensitivities for Glioma, Meningioma, Pituitary, and Normal Tumor indicate the proportion of True Positive cases correctly identified for each category.

The **F1-score** is a measure of the model's accuracy, taking into account both precision and sensitivity. A high F1-score of **99.00%** suggests that the model achieves a good balance between precision and sensitivity.

The **AUC** (**Area Under the Curve**) as depicted in Figure 7.5 is a metric commonly used to assess the performance of binary classifiers. An AUC value of **1.0** indicates that the model has achieved perfect discrimination between positive and negative cases.

Overall, these results demonstrate the potential of the ResNet50 model as a valuable tool in assisting medical professionals in diagnosing brain tumors. However, it is crucial to continue refining the model and conducting further evaluation to ensure its robustness and applicability in real-world scenarios.

Chapter 8

CONCLUSION AND FUTURE WORK

8.1 Conclusion

In conclusion, this work focused on developing a Brain Tumor Prediction system utilizing a Deep Learning Network, specifically the ResNet50 model. Through rigorous experimentation and evaluation, highly promising results have been achieved. The model exhibited exceptional performance, showcasing an impressive accuracy of 98.78%, precision of 99.0%, F1 score of 99.0%, and an AUC (Area Under the Curve) value of 1.0. These metrics highlight the model's robustness and its ability to accurately classify brain tumor images into different categories.

The utilization of deep learning techniques, combined with the ResNet50 architecture, proved to be effective in extracting meaningful features and patterns from brain tumor images, enabling accurate predictions. By leveraging a large and diverse dataset, the model learned to distinguish between Meningioma, Pituitary, Glioma and No tumor categories with remarkable precision.

However, it is important to acknowledge the limitations of the project. While this model demonstrated outstanding performance, further validation on larger and more diverse datasets is necessary to ensure its generalization capabilities. Additionally, the interpretability of the model's decision-making process remains an ongoing challenge in the field of deep learning.

8.2 Future Work

Though the project has achieved remarkable results and developed a reliable model, there are several avenues for future work and enhancements that can be explored to further improve the effectiveness and applicability of the system.

(i) **Ensemble Models**: Combining ResNet-50 with other deep learning models or traditional machine learning algorithms can create powerful ensemble models, improving classification accuracy and robustness.

(ii) **Explainable AI**: Developing methods to explain the model's predictions and decisions can increase trust and acceptance in clinical settings, facilitating its adoption by medical professionals.

(iii) **Real-Time Diagnosis**: Optimizing ResNet-50 for real-time processing can enable its integration into imaging systems, facilitating immediate diagnosis and enhancing the efficiency of brain tumor detection.

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