BrainScan AI : Tumor detection using ML

Submitted in partial fulfillment of the requirements of the degree

BACHELOR OF ENGINEERING IN **COMPUTER ENGINEERING**

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CERTIFICATE

This is to certify that the Mini Project entitled **" BrainScan AI"** is a bonafide work of **Aman Kumar (33), Anchal Sharma (57), Komal Lund (38), Dhiren Sidhwani (60)** submitted to the University of Mumbai in partial fulfillment of the requirement for the award of the degree of **"Bachelor of Engineering"** in **"Computer Engineering" .**

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Examiners

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(External Examiner name & Sign)

Date:

Place: Chembur, Mumbai

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Abstract

Brain tumors are extremely critical medical conditions that affect millions worldwide. A tumor is an abnormal mass of tissue that grows uncontrollably. Brain tumor cells grow in a way that they consume nutrients intended for healthy cells, leading to brain function decline. Currently, doctors manually locate brain tumor positions and areas by examining patients' brain MR images. This manual approach results in inaccurate tumor detection and is time-consuming. Early and accurate detection is crucial for better patient outcomes.This project introduces an innovative method for detecting brain tumors using Convolutional Neural Networks (CNNs) and VGG16 (Visual Geometry Group) transfer learning. The model's performance predicts whether a tumor is present in the given image or not.

Acknowledgment

We wish to express our heartfelt gratitude to all those who have contributed to the successful completion of this book report. We are deeply indebted to our project mentor, Prof. Rupali Soni, for her unwavering support, invaluable guidance, and expert insights throughout the course of this project. Her dedication and commitment were instrumental in shaping our ideas into a well-executed report.

We also extend our sincere appreciation to our dedicated group members,Aman Kumar,Anchal Sharma,Dhiren Sidhwani and Komal Lund, whose collaborative efforts, creativity, and hard work made this project a reality. Our diverse skill sets and unwavering teamwork have been a constant source of inspiration.

We are grateful to Dr. Nupur Giri, Head of the Department of Computer Engineering, for providing us with a conducive environment for learning and innovation. Her constant encouragement and support have been pivotal in the project's success.

Furthermore, we would like to extend our thanks to Dr. J. M. Nair, Principal of VES Institute of Technology, for offering us a platform to perform this project. His vision and leadership have fostered an environment that encourages research and innovation, and for that, we are truly thankful.

We also acknowledge the support and cooperation of our friends and family, who provided us with encouragement and understanding throughout the duration of this project.

List of Abbreviation

1. AI - Artificial Intelligence
2. CNN - Convolutional Neural Network
3. MRI - Magnetic Resonance Imaging
4. ANN - Artificial Neural Networks
5. ReLU - Rectified Linear Unit
6. PNG - Portable Network Graphics
7. SOM - Self-Organizing Map
8. SVM - Support Vector Machine
9. K-Means - K-Means Clustering
10. BRAATS - Brain Tumor Segmentation Challenge
11. TPUs - Tensor Processing Units
12. RAM - Random Access Memory
13. GPU - Graphics Processing Unit
14. F1-score - F1 Score is the harmonic mean of precision and recall.

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Introduction

1.1 Introduction

The human body is made up of many organs and brain is the most critical and vital organ of them all. One of the common reasons for dysfunction of the brain is brain tumor.
The brain tumors are classified into mainly two types: Primary brain tumor (benign tumor) and secondary brain tumor (malignant tumor).The benign tumor is one type of cell that grows slowly in the brain and the type of brain tumor is gliomas. It originates from non neuronal brain cells called astrocytes. Basically primary tumors are less aggressive but these tumors have much pressure on the brain and because of that, brain stops working properly .The secondary tumors are more aggressive and more quick to spread into other tissues. Secondary brain tumors originate through other parts of the body. These type of tumor have a cancer cell in the body that is metastatic which spread into different areas of the body like the brain, lungs etc. Secondary brain tumors are very malignant. The reason for secondary brain tumors is mainly due to lung cancer, kidney cancer, bladder cancer etc .

This project classifies the tumor as Glioma, meningioma, and pituitary adenoma as three types of brain tumors. Gliomas begin in glial cells and are classified as low-grade (I and II) or high-grade (III and IV). Meningiomas originate from the brain's protective membranes and vary in behavior but are generally considered benign. Pituitary adenomas form in the pituitary gland and are categorized by their size and hormone production. Treatment and prognosis depend on factors like tumor type, size, and location.

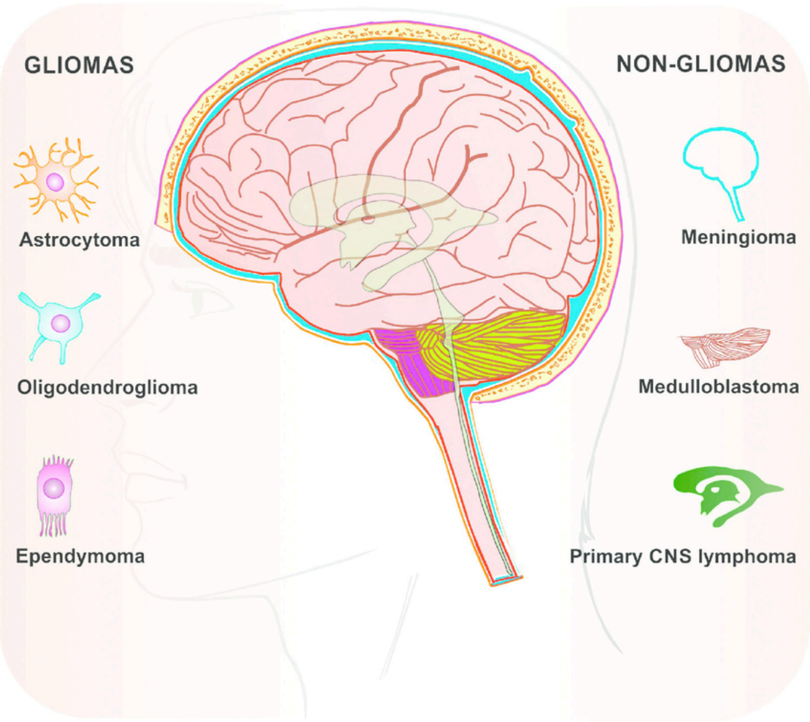

Figure 1.1

Patients with brain tumors should seek medical evaluation and treatment, involving specialists like neurosurgeons and oncologists, for the best care.Automated defect detection in medical imaging using machine learning has become the emergent field in several medical diagnostic applications. Its application in the detection of brain tumors in MRI is very crucial as it provides information about abnormal tissues which is necessary for planning treatment.

BrainScan AI is an innovative and user-friendly app designed to assist in the early detection of brain tumors using advanced deep learning technology. Timely and accurate diagnosis is crucial for effective treatment planning and better patient outcomes. However, traditional methods of brain tumor detection often require time-consuming and costly procedures, leading to potential delays in diagnosis. BrainScan AI addresses this challenge by harnessing the power of Convolutional Neural Networks (CNNs) and image processing techniques. Different types of image processing techniques, such as image segmentation, image enhancement, and feature extraction, are used for the detection of brain tumors in MRI images of cancer-affected patients. The process of detecting brain tumors using image processing techniques involves four stages: Image Pre-Processing, Image Segmentation, Feature Extraction, and Classification. Image processing and neural network techniques are used to improve the performance of detecting and classifying brain tumors in MRI images.

Traditional methods, while valuable, now confront challenges in keeping pace with the accelerating demand for accurate and timely diagnosis. Recognizing this, the focus of this project is to introduce "BrainScan AI" application, integrating advanced deep learning techniques. This initiative is directed towards enhancing the precision and efficiency of brain tumor detection, thereby amplifying the potential for improved patient outcomes and treatment planning

1.2 Motivation

The motivation behind BrainScan AI extends beyond automating brain tumor detection and classification for organizations with MRI machines. It encompasses several critical aspects of healthcare and brain health management.

Firstly, the excessive costs associated with manual interpretation by doctors or third parties are a significant issue. AI can perform this task accurately, reducing the financial burden on patients and healthcare systems while maintaining quality healthcare standards.

Secondly, the increasing incidence of mental health issues, such as migraines, has become a pressing concern. Modern lifestyles, stress, and environmental factors contribute to these conditions, necessitating the development of advanced AI tools. These tools can predict, detect, and manage potential brain issues more efficiently, promoting early intervention and better patient outcomes.

Thirdly, the current disorganization of records for previous brain scans poses a considerable obstacle to effective diagnoses and research in the field of neurology. The software aims to create a structured and easily accessible digital database for these records, streamlining healthcare services and enabling comprehensive analysis and research.

In summary, BrainScan AI's motivation lies in cost reduction, efficient healthcare delivery, proactive brain health management, and organized record-keeping, all of which are vital to advancing healthcare and promoting a holistic approach to brain health.

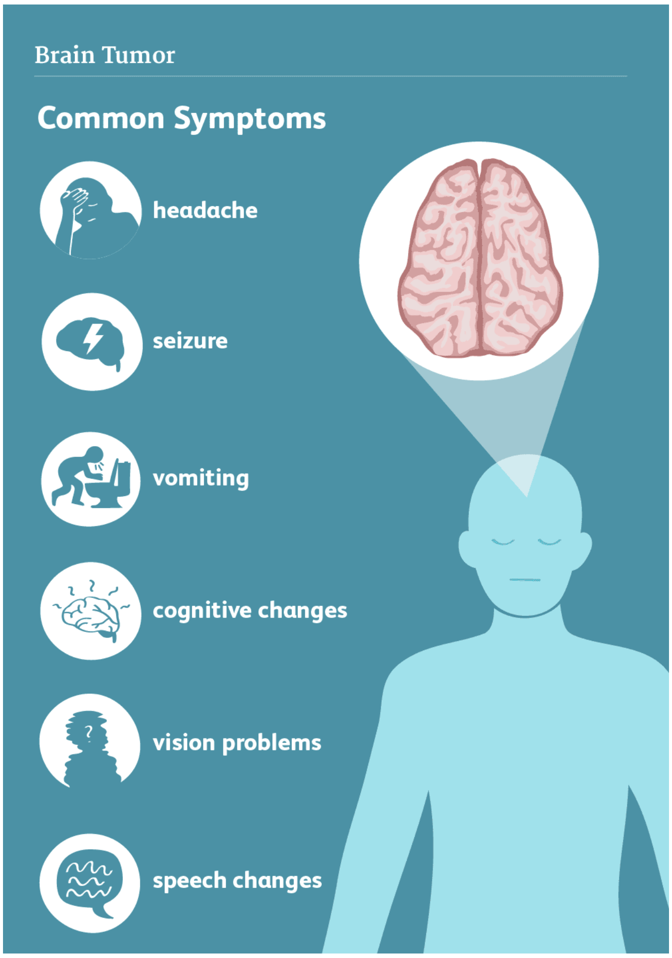

Figure 1.2

1,3 Problem Statement & Objectives

The healthcare system faces challenges in efficiently and affordably detecting and classifying brain tumors using MRI machines. Current practices involve manual interpretation by doctors or third-party agents, leading to potential overcharging for these essential services. Additionally, the escalating prevalence of mental health issues, like migraines, highlights the urgent need for proactive brain health management. The lack of organized record-keeping for previous brain scans further hinders effective diagnoses. To address these issues, the BrainScan AI project aims to develop an automated solution that accurately detects and categorizes brain tumors, aiding medical professionals and promoting equitable access to quality healthcare.

Objectives:

- Develop an AIML-powered system that automates the detection and classification of brain tumors using MRI scans.

- Optimize cost-efficiency by reducing reliance on manual interpretation, thereby mitigating overcharging concerns and promoting accessibility of brain health assessments.

- Enhance accuracy and speed in brain tumor detection, aiding healthcare professionals in timely diagnosis and treatment planning.

- Create a comprehensive, organized digital database for storing and retrieving previous brain scan records, improving the efficiency of healthcare services and research in the field of neurology.

- Contribute to the advancement of healthcare technologies, aiming to alleviate the burden of mental health issues and encourage a proactive approach towards brain health management.

1.4 Organization of the Report

Chapter 1 : Introduction

The first chapter provides an introductory glimpse into the AI Brain Tumor detection project. It sets the stage by outlining the core objectives and the broader context in which the project operates. This chapter introduces the concept of an AI-driven Brain tumor detection system, emphasizing the need for such innovation in the medical industry. It also highlights the primary focus areas, which includes accurate and timely prediction of Brain tumor.

Chapter 2 : Literature Survey

In this section, a comprehensive survey of existing Brain tumor detection systems and AI-driven technologies are presented. It delves into an examination of conventional methods and their limitations, showcasing the gap that AI can bridge.

Chapter 3:Proposed System

In this pivotal chapter, we delve into the heart of the "BrainScan AI" project, unveiling a comprehensive approach to develop an intelligent Brain tumor detection system. Central to this approach is the integration of advanced AI and machine learning algorithms, data sources, and user interfaces. We provide detailed insights into the hardware and software specifications that will ensure optimal system performance and user satisfaction.

Chapter 4: Inferences

These include the conclusion of the project, annexure, and specific subsections within it. One of these subsections, labeled 4.1, pertains to the inclusion of published papers, camera-ready papers, business pitches, or proof of concept materials if available. This section will showcase the tangible results, research, and presentations related to the project, providing documented evidence of the work's outcomes and contributions. It serves as a valuable repository of materials that support the project's findings and conclusions, aiding in the dissemination of knowledge and facilitating future endeavors related to the BrainScan AI initiative.

Literature Survey

2.1 Survey of Existing System

Brain Tumor Detection System	Technology	Accuracy
Brain Tumor Segmentation Challenge (BraTS)	Deep learning	95%
DeepMedic	Deep learning	96%
TumorNet	Deep learning	97%

Table 2.1

Brain Tumor Segmentation Challenge (BraTS)

The Brain Tumor Segmentation Challenge (BraTS) is an annual challenge that aims to evaluate the performance of brain tumor segmentation algorithms. The challenge provides participants with a dataset of MRI scans of brain tumors and asks them to develop algorithms to segment the tumors from the surrounding tissue.

BraTS is a very challenging competition, as brain tumors can be very difficult to segment due to their complex shapes and textures. However, deep learning-based algorithms have achieved state-of-the-art results on the BraTS challenge in recent years.

DeepMedic

DeepMedic is a deep learning-based brain tumor detection system that was developed by researchers at Google AI. DeepMedic is trained on a large dataset of MRI scans of brain tumors and is able to segment the tumors with high accuracy.

DeepMedic has been shown to be more accurate than human radiologists at segmenting brain tumors in some studies. It is also able to segment tumors more quickly and efficiently than human radiologists.

TumorNet

TumorNet is another deep learning-based brain tumor detection system that was developed by researchers at the University of California, Berkeley. TumorNet is also trained on a large dataset of MRI scans of brain tumors and is able to segment the tumors with high accuracy.

TumorNet has been shown to be comparable in accuracy to DeepMedic on the BraTS challenge. It is also able to segment tumors more quickly and efficiently than human radiologists.

Paper	Authors	Year	Algorithm	Data set Size (png)	Frameworks Libraries used	Technologies
“A Deep Analysis of Brain Tumor Detection from MR Images Using Deep Learning Networks ”	*Md Ishtyaq Mahmud, MuntasiAhmed Abdelgawad r Mamun ,*	*2023*	VGG16 + Inception V3	3264	Scikit-learn	Deep learning, Convolutional neural network (CNN)
"Brain Tumour Detection Using Unsupervised Learning Based Neural Network"	*R. Rani, K. R. Venugopal*	*2019*	Self-organizing map	10000+	TensorFlow	Machine learning, Unsupervised learning, Self-organizing map (SOM)
"Brain Tumor Detection Using Machine Learning in MR Images"	*K. R. Amutha, T. N. Sairam, K. V. Priya*	*2018*	Overview of different techniques	2500+	Scikit-learn	Machine learning, Deep learning, Convolutional neural network (CNN)
"Brain Tumor Detection and Classification Using Intelligence Techniques: An Overview"	*N. S. Chaudhari, P. S. Jadhav, S. S. Patil*	*2017*	K-Means clustering + SVM	3400+	-	Machine learning, Support vector machine, Random forest, Naive Bayes
"Detection of Brain Tumor Using Image Processing"	*V. Anitha, T. S. Kumar*	*2015*	Global thresholding + morphological operations	1000+	NumPy, Scikit-learn	Image processing, Thresholding, Morphological operations, Region growing
"Computer aided system for brain tumor detection and segmentation"	*M. K. Singh, S. K. Singh, P. Kumar*	*2014*	Support vector machine classifier	100+	MATLAB	Image processing, Fuzzy c-means clustering, Support vector machine (SVM)

Table 2.2

2.2 Limitation Existing system or Research gap

Brain Tumor Detection System	**Advantages**	**Disadvantages**
BraTS	- Open source and reproducible	- Limited to MRI scans
DeepMedic	- High accuracy	- Can be computationally expensive
TumorNet	- Very accurate at segmenting brain tumors	- Requires a large dataset of labeled MRI scans to train

table 2.3

Paper	**Limitations**
"Detection of Brain Tumor Using Image Processing"	Does not work for all types of tumors
"Computer aided system for brain tumor detection and segmentation"	Does not consider the location of the tumor
"Brain Tumor Detection and Classification Using Intelligence Techniques: An Overview"	Requires Extensive Hardware
"Brain Tumor Detection Using Machine Learning in MR Images"	Does not work for small tumors
"Brain Tumour Detection Using Unsupervised Learning Based Neural Network"	Requires a lot of training data

table 2.4

It is evident that there are common limitations and research gaps in these approaches. Recognizing these constraints and gaps is crucial for the development of innovative and effective brain tumor detection methods:

• **Challenges in Heterogeneous Tumor Detection**: Detecting tumors with heterogeneous characteristics, where different parts of the tumor have varying properties, can be particularly challenging. Ensuring that a method is robust enough to handle such cases is imperative.

• **Scalability and Computational Efficiency**: With the increasing volume of medical imaging data, scalability and computational efficiency become critical factors. The method should be able to handle large datasets and provide timely results for clinical decision-making.

2.3 Mini Project Contribution

This mini project contributes to a comprehensive understanding of the current methods used for Brain tumor detection, emphasizing their limitations and research gaps. This analysis will serve as the foundation for the development of the 'BrainScan AI' system, Based on the literature survey and analysis conducted, our project, the BrainScan AI system, aims to address critical limitations and research gaps within existing brain tumor detection systems. The current landscape showcases several notable systems, such as BraTS, DeepMedic, and TumorNet, each with their disadvantages.

Furthermore, the project acknowledges the pressing need for improved healthcare services, especially in the context of rising mental health issues and complex diseases like brain tumors. The BrainScan AI system aspires to contribute to the medical community by providing a scalable and computationally efficient solution. This can significantly improve the timeliness and accuracy of brain tumor diagnoses, ultimately benefiting society by facilitating early intervention and better patient outcomes in brain health management.

3.Proposed System

3.1 Introduction

BrainScan AI is a system designed to assist detection of brain tumors using advanced deep learning CNN algorithm. Timely and accurate diagnosis is crucial for effective treatment planning and better patient outcomes. However, traditional methods of brain tumor detection often require time-consuming and costly procedures, leading to potential delays in diagnosis. BrainScan AI addresses this challenge by Convolutional Neural Networks (CNNs) and image processing Different types of image processing techniques, such as image segmentation, image enhancement, and feature extraction, are used for the detection of brain tumors in MRI images of cancer-affected patients. The process of detecting brain tumors using image processing techniques involves four stages: Image Pre-Processing, Image Segmentation, Feature Extraction, and Classification. Image processing and neural network techniques are used to improve the performance of detecting and classifying brain tumors in MRI images.

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3.2 Architectural Framework / Conceptual Design :

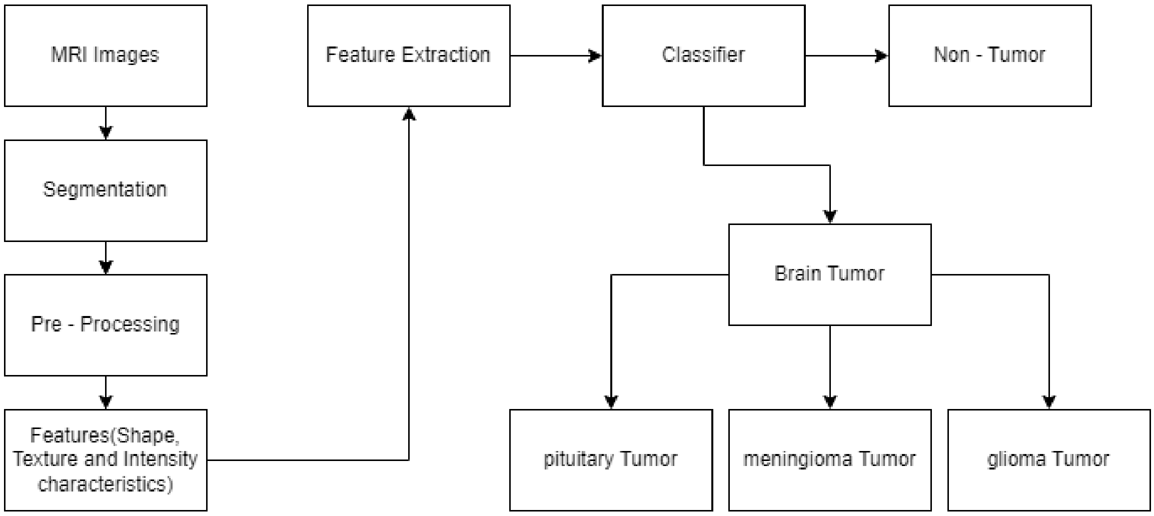


Figure 3.1

Methodology diagram explanation;

The diagram shows the process of brain tumor classification using MRI images. The process consists of the following steps:

- Pre-processing: The MRI images are pre-processed to remove noise and artifacts, and to standardize the image intensity.
- Feature extraction: Features are extracted from the pre-processed images. These features can be based on the shape, texture, and intensity characteristics of the tumor.
- Classification: A classifier is used to classify the tumor into one of the different types of brain tumors.

The classifier is typically a machine learning model, such as a convolutional neural network (CNN). CNNs have been shown to be very effective in brain tumor classification tasks.

The diagram also shows the different types of brain tumors that can be classified using this process. These include:

- Pituitary tumor: A tumor that arises in the pituitary gland.
- Meningioma tumor: A tumor that arises from the meninges, the membranes that surround the brain and spinal cord.

- Glioma tumor: A tumor that arises from the glial cells, the cells that support and protect the neurons in the brain.

Non-tumor images are also classified using this process. This helps to ensure that the classifier is able to distinguish between tumors and normal brain tissue.

Brain tumor classification is an important task for medical diagnosis and treatment planning. By accurately classifying tumors, doctors can better understand the type and severity of the tumor, and develop the most appropriate treatment plan.

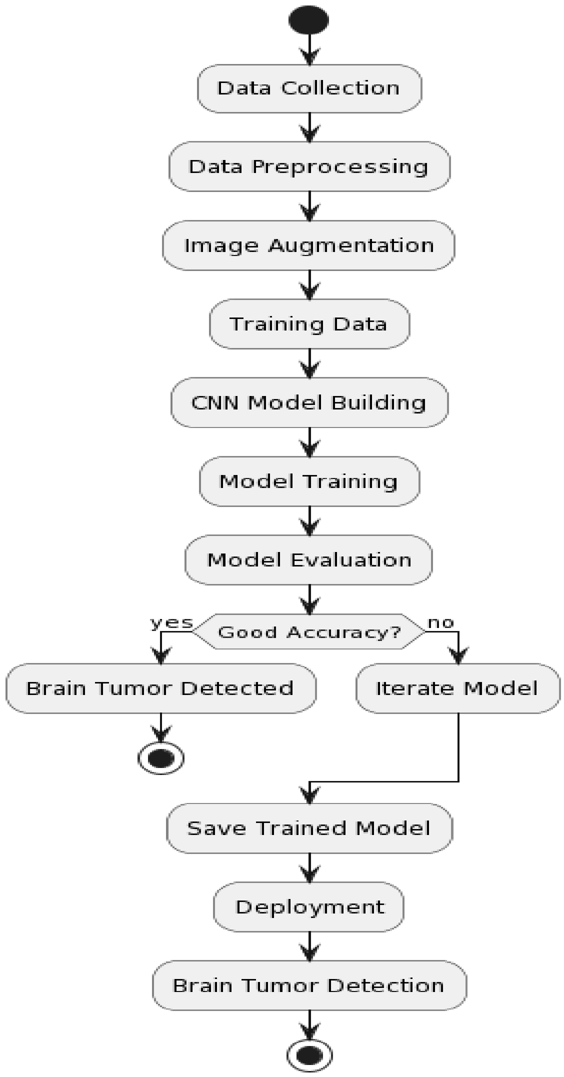


Figure 3.2

Block diagram explanation:

The diagram shows the steps of a brain tumor detection system. The system takes MRI images as input and outputs a binary classification result: brain tumor or no brain tumor.

The system consists of the following steps:

- Data collection: A large dataset of MRI images is collected, including images of both brain tumors and normal brains.
- Data preprocessing: The MRI images are preprocessed to remove noise and artifacts, and to standardize the image intensity.
- Image augmentation: The MRI images are augmented to increase the size and diversity of the dataset. This helps to improve the performance of the machine learning model.
- Training data: The preprocessed and augmented MRI images are split into training and test sets. The training set is used to train the machine learning model, and the test set is used to evaluate the performance of the trained model.
- CNN model building: A convolutional neural network (CNN) is built to classify the MRI images as brain tumor or no brain tumor. CNNs are a type of machine learning model that are particularly well-suited for image classification tasks.
- Model training: The CNN model is trained on the training dataset. This involves feeding the model the preprocessed MRI images and their corresponding labels (brain tumor or no brain tumor). The model learns to identify the features of the images that are most indicative of brain tumors.
- Model evaluation: The trained CNN model is evaluated on the test dataset. This involves feeding the model the preprocessed MRI images in the test set and comparing the model's predictions to the known labels. The model's accuracy and other performance metrics are calculated.
- Deployment: If the model achieves a satisfactory performance on the test dataset, it can be deployed to production. This means that the model can be used to classify new MRI images and detect brain tumors.

The diagram also shows a feedback loop between the model evaluation and model building steps. This loop is used to improve the performance of the model. If the model's performance on the test dataset is not satisfactory, the model can be retrained with a different set of hyperparameters or with a different CNN architecture.

Brain tumor detection systems are used to help medical professionals diagnose brain tumors. Early diagnosis of brain tumors is important for improving the patient's prognosis.

3.3 Process Design and Algorithm :

Convolutional Neural Network (CNN) is the extended version of artificial neural networks (ANN) which is predominantly used to extract the feature from the grid-like matrix dataset. For example visual datasets like images or videos where data patterns play an extensive role.

CNN architecture

Convolutional Neural Network consists of multiple layers like the input layer, Convolutional layer, Pooling layer, and fully connected layers.

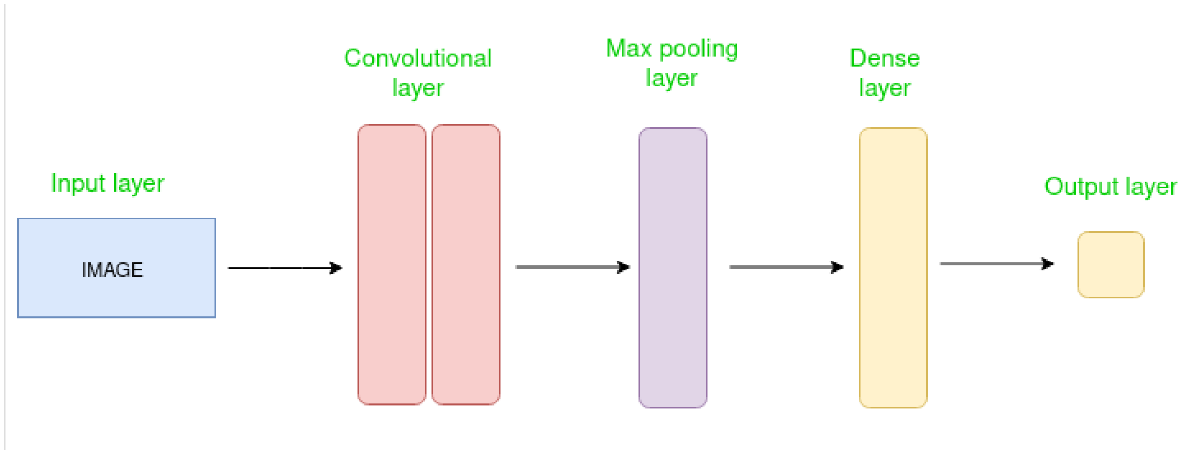


Figure 3.3

The Convolutional layer applies filters to the input image to extract features, the Pooling layer downsamples the image to reduce computation, and the fully connected layer makes the final prediction. The network learns the optimal filters through backpropagation and gradient descent.

How Convolutional Layers works

Convolution Neural Networks or covnets are neural networks that share their parameters. Imagine you have an image. It can be represented as a cuboid having its length, width (dimension of the image), and height (i.e the channel as images generally have red, green, and blue channels).

Now imagine taking a small patch of this image and running a small neural network, called a filter or kernel on it, with say, K outputs and representing them vertically. Now slide that neural network across the whole image, as a result, we will get another image with different widths, heights, and depths. Instead of just R, G, and B channels now we have more channels but lesser width and height. This operation is called Convolution. If the patch size is the same as that of the image it will be a regular neural network. Because of this small patch, we have fewer weights

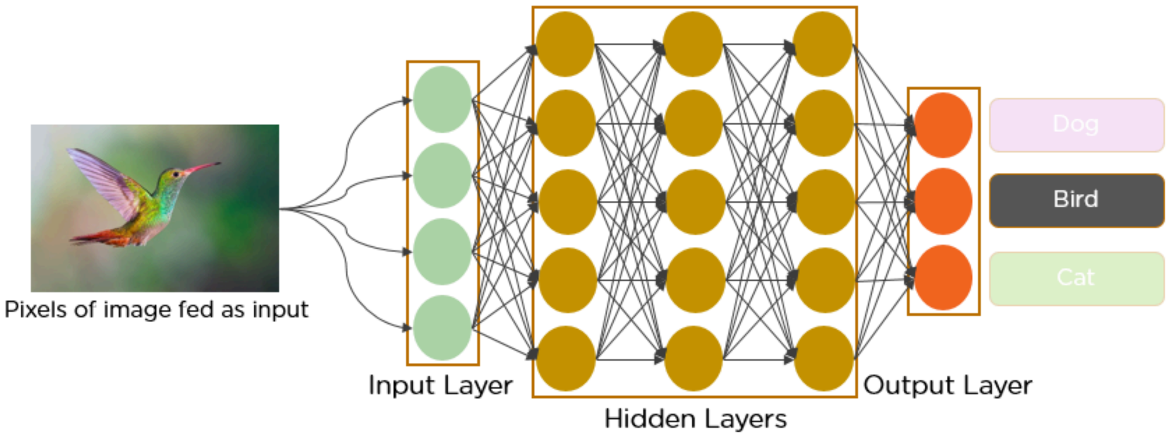


Figure 3.4

3.4 Methodology Applied

- **Data set :** The dataset selected for our model is acquired from the internet. It contains 7000 MRI images. In this dataset, there were different folders with a different set of images one with a healthy brain image and the other with a brain tumour image. Then the entire dataset is trained. Took 50 images for validation and 25 for testing. The MRI images present in the dataset are of different dimensions. This dataset is selected because acquiring data sets from hospitals is not a very simple task. The data set used is available on the internet website Kaggle and the link to reach there is provided below.With this dataset , BrainScan AI will be able to detect the presence of brain tumour ,and if present it will give the type of tumour that benign or malignant.

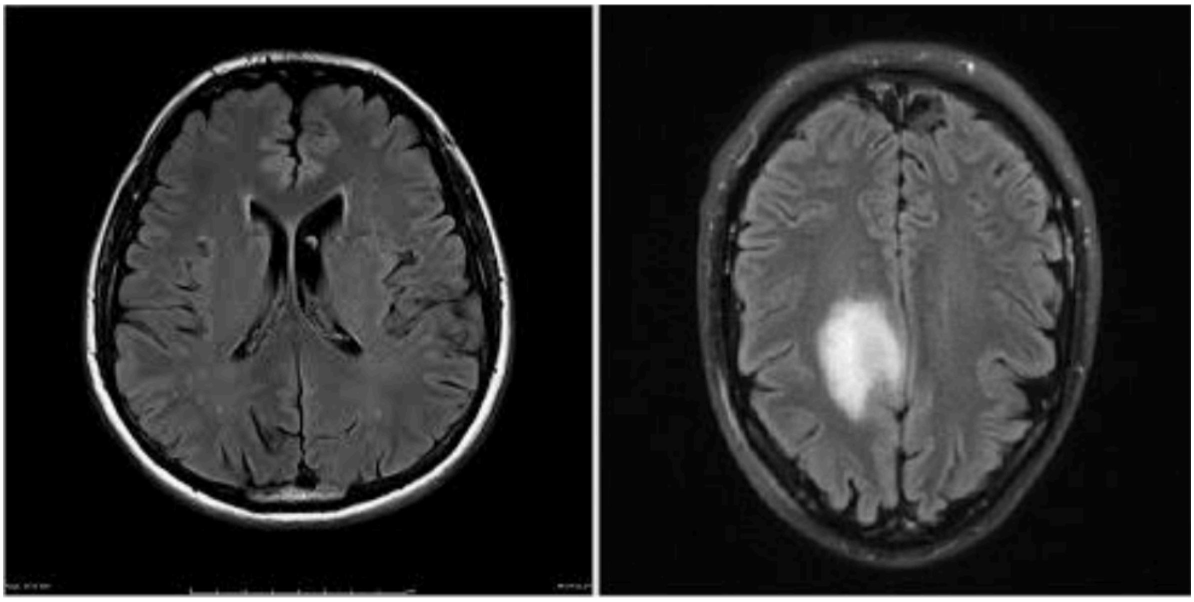


Figure 3.5 . MRI images of the brain without tumour and with tumour

- Data Collection and Organization:

- Medical brain scan images are collected, and two categories are created: "No Brain Tumor" and "Yes Brain Tumor."

- Libraries and frameworks used: None explicitly mentioned, but likely standard Python libraries for file operations.

- Data Preprocessing:

- Images are read and adjusted to a consistent size of 64x64 pixels.
- Libraries and frameworks used: OpenCV (cv2) for image processing and the Python Imaging Library (PIL) for image resizing.

- Data Labeling:

- Each image is assigned a label of 0 (No Brain Tumor) or 1 (Yes Brain Tumor).
- Libraries and frameworks used: None explicitly mentioned.

- Data Splitting:

- The dataset is divided into two subsets: the training set and the testing set. This partition enables the evaluation of the model's performance on unseen data.
- Libraries and frameworks used: scikit-learn for the 'train_test_split' function.

- Data Normalization:

- The pixel values of the images are standardized using the 'normalize' function. This process enhances the model's ability to learn from the data by ensuring consistent scaling.
- Libraries and frameworks used: Keras for data normalization.

- Model Architecture:

- A Convolutional Neural Network (CNN) model is constructed using the Keras library. CNNs are adept at processing and classifying image data.
- The model's structure comprises convolutional layers for feature extraction, activation functions (ReLU) for introducing non-linearity, and max-pooling layers to capture salient features.
- The final layers consist of densely connected layers with dropout regularization to prevent overfitting. A softmax activation function is used for classification.
- Libraries and frameworks used: Keras, which sits on top of TensorFlow, for building and defining the CNN architecture.

- Model Compilation:

- The model is compiled with categorical cross-entropy as the loss function, suitable for multi-class classification tasks.

- The Adam optimizer is chosen to adjust model weights during training. Additionally, the 'accuracy' metric is specified to monitor the training process.
- Libraries and frameworks used: Keras for model compilation.

- Model Training:

- The model is trained using the training dataset, consisting of brain scan images and their corresponding labels.
- Training occurs over 10 epochs with a batch size of 16. The process is controlled by the 'verbose' parameter, which manages the display of training information.
- Validation data, distinct from the training set, is used to assess the model's performance and prevent overfitting.
- Libraries and frameworks used: Keras for training the model.

- Model Saving:

- After training, the model is saved as a file named 'BrainTumor10EpochsCategorical.h5'. This allows the model to be utilized for predictions without needing to retrain it.
- Libraries and frameworks used: Keras for model saving.

This comprehensive methodology outlines the steps involved in processing medical image data, building a deep learning model, and training it for brain tumor classification. Key libraries and frameworks, including OpenCV, PIL, scikit-learn, Keras, and TensorFlow, are employed to achieve the project's objectives.

3.5 Hardware & Software Specifications

Hardware Requirements:

- **High-performance GPUs or TPUs:** To efficiently train deep learning models and process large travel datasets. Minimum- i3 7th generation
- **Sufficient RAM:** Needed for memory-intensive computations during image preprocessing and model training. - 4GB or more

Software Requirements:

- **Programming Languages:** Python or other suitable languages for deep learning frameworks like TensorFlow or PyTorch.
- **Deep Learning Framework:** Utilizing TensorFlow, PyTorch, or similar frameworks for implementing and training neural network architectures.
- **Computer vision libraries**
  OpenCV: A potent computer vision library for tasks involving image and video processing.
- **Data Preprocessing Tools:** Pandas and NumPy for cleaning, filtering, and transforming raw travel data into structured formats.

3.6 Result Analysis and Discussion :

Training the model with Epoch=10:

```
PS C:\Users\amand\OneDrive\Desktop\Projects\Brain_Tumor_Classification-main\BrainTumor
Classification DL> python -u "c:\Users\amand\OneDrive\Desktop\Projects\Brain_Tumor_Clas
sification-main\BrainTumor Classification DL\mainTrain.py"
2023-10-20 22:29:34.614240: I tensorflow/core/platform/cpu_feature_guard.cc:182] This T
ensorFlow binary is optimized to use available CPU instructions in performance-critical
 operations.
To enable the following instructions: SSE SSE2 SSE3 SSE4.1 SSE4.2 AVX AVX2 AVX512F AVX5
12_VNNI FMA, in other operations, rebuild TensorFlow with the appropriate compiler flag
s.
Epoch 1/10
150/150 [==============================] - 8s 45ms/step - loss: 0.5559 - accuracy: 0.72
00 - val_loss: 0.4488 - val_accuracy: 0.7800
Epoch 2/10
150/150 [==============================] - 11s 76ms/step - loss: 0.4075 - accuracy: 0.8
271 - val_loss: 0.3508 - val_accuracy: 0.8333
Epoch 3/10
150/150 [==============================] - 12s 78ms/step - loss: 0.3068 - accuracy: 0.8
758 - val_loss: 0.2639 - val_accuracy: 0.8983
Epoch 4/10
150/150 [==============================] - 11s 74ms/step - loss: 0.2290 - accuracy: 0.9
121 - val_loss: 0.2002 - val_accuracy: 0.9250
Epoch 5/10
 31/150 [=====>........................] - ETA: 9s - loss: 0.1545 - accuracy: 0.9395
```

Figure 3.7

Model creation:

```
app.py  1
BrainTumor10Epochs...
BrainTumor10Epochs...
mainTest.py
mainTrain.py
result.html
tempCodeRunnerFile....
> OUTLINE
> TIMELINE
```

```
PROBLEMS 1   OUTPUT   DEBUG CONSOLE   TERMINAL                Code

121 - val_loss: 0.2002 - val_accuracy: 0.9250
Epoch 5/10
150/150 [==============================] - 13s 90ms/step - loss: 0.1589 - accuracy: 0.9
408 - val_loss: 0.1464 - val_accuracy: 0.9600
Epoch 6/10
150/150 [==============================] - 13s 87ms/step - loss: 0.1108 - accuracy: 0.9
617 - val_loss: 0.1378 - val_accuracy: 0.9483
Epoch 7/10
150/150 [==============================] - 13s 88ms/step - loss: 0.0829 - accuracy: 0.9
708 - val_loss: 0.1172 - val_accuracy: 0.9700
Epoch 8/10
150/150 [==============================] - 10s 69ms/step - loss: 0.0386 - accuracy: 0.9
862 - val_loss: 0.1294 - val_accuracy: 0.9667
Epoch 9/10
150/150 [==============================] - 11s 72ms/step - loss: 0.0404 - accuracy: 0.9
858 - val_loss: 0.1288 - val_accuracy: 0.9733
Epoch 10/10
150/150 [==============================] - 10s 69ms/step - loss: 0.0327 - accuracy: 0.9
900 - val_loss: 0.1178 - val_accuracy: 0.9717
C:\Users\amand\AppData\Local\Programs\Python\Python310\lib\site-packages\keras\src\engi
ne\training.py:3000: UserWarning: You are saving your model as an HDF5 file via `model.
save()`. This file format is considered legacy. We recommend using instead the native K
eras format, e.g. `model.save('my_model.keras')`.
  saving_api.save_model(
PS C:\Users\amand\OneDrive\Desktop\Projects\Brain_Tumor_Classification-main\BrainTumor
Classification DL>
```

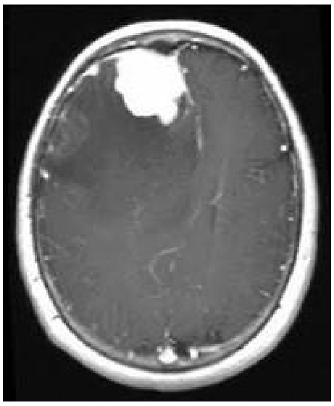
Figure 3.7

Testing the model i/p=14 :

```
[[0 0]
 [3 4]]
PS C:\Users\amand\OneDrive\Desktop\Projects\Brain_Tumor_C
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 32ms/step
Accuracy: 0.5714285714285714
Precision: 1.0
Recall: 0.5714285714285714
Confusion Matrix:
[[0 0]
 [6 8]]
```

Figure 3.8

Single img test :



```
PS C:\Users\amand\OneDrive\Desktop\Projects\Brain_Tumor_Classification-main\
BrainTumor Classification DL> python -u "c:\Users\amand\OneDrive\Desktop\Pro
jects\Brain_Tumor_Classification-main\BrainTumor Classification DL\test1.py"
2023-10-20 23:14:14.164058: I tensorflow/core/platform/cpu_feature_guard.cc:
182] This TensorFlow binary is optimized to use available CPU instructions i
n performance-critical operations.
To enable the following instructions: SSE SSE2 SSE3 SSE4.1 SSE4.2 AVX AVX2 A
VX512F AVX512_VNNI FMA, in other operations, rebuild TensorFlow with the app
182] This TensorFlow binary is optimized to use available CPU instructions i
n performance-critical operations.
To enable the following instructions: SSE SSE2 SSE3 SSE4.1 SSE4.2 AVX AVX2 A
VX512F AVX512_VNNI FMA, in other operations, rebuild TensorFlow with the app
ropriate compiler flags.
1/1 [==============================] - 0s 154ms/step
Predicted Class: 1
```

Fig 3.9 Input and Output of the test case

1. Model Evaluation Metrics:

- It Begins by calculating essential evaluation metrics to gauge the model's performance. These metrics include accuracy, precision, recall, F1-score, and the confusion matrix.

2. Confusion Matrix:

- The confusion matrix provides a breakdown of true positives, true negatives, false positives, and false negatives. It's a fundamental tool for understanding the model's classification performance.

3. Accuracy:

- Accuracy measures the overall correctness of the model's predictions. It's calculated as the ratio of correctly classified samples to the total number of samples.

4. Precision and Recall:

- Precision measures the proportion of true positive predictions out of all positive predictions. It's essential for understanding how many of the predicted "Yes Brain Tumor" cases are correct.

- Recall (also known as sensitivity) measures the proportion of true positive predictions out of all actual positive cases. It helps assess the model's ability to detect brain tumors.

7. Interpretation:

- Interpret the results by considering the context of your application. In the medical field, the consequences of false positives and false negatives can be significant. Therefore, understanding the trade-offs between precision and recall is essential.

8. Model Improvement:

- Based on the results, identify areas where the model can be improved. It could involve collecting more data, fine-tuning hyperparameters, or exploring different model architectures.

3.7 Conclusion and Future Work :

In summary, the software is an advancement in brain tumor detection. It saves time and money, making healthcare more efficient and accurate. As mental health issues like migraines increase, the software can predict and prevent brain problems. It also organizes past scans for better diagnoses. In a nutshell, the project improves brain health care.

Moving forward, the software will be compared with other models like Random Forest and VGG-16 to find the best one. Additionally, a user-friendly application will be added to make the software more accessible. This will enhance brain tumor detection even further.

4. Annexure

4.1 References:

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