CERTIFICATE

*This is to certify that the work contained in this thesis entitled "**BRAIN TUMOR DETECTION AND CLASSIFICATION SYSTEM USING DEEPNETS**" is a bonafide work of **Govind Singh (34230820010)** carried out in the Department of Computer Science and Engineering : Artificial Intelligence and Machine Learning, Future Institute of Technology, Boral, Kolkata, under my supervision and that it has not been submitted elsewhere for a degree.*

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Last but not the least, we would like to acknowledge all the authors and researchers whose work provided a foundation and context for our study. This has been instrumental for our understanding and approach to this topic.

ABSTRACT

Nowadays, tumor is the second leading cause of cancer. Brain tumor is one of the most challenging and life-threatening medical conditions to diagnose and treat. The increasing prevalence of brain tumors demand advanced diagnostic tools for timely and accurate detection as well as proper classification for effective treatment planning and patient outcomes. Detection plays very important role in treatment. If proper detection of tumor is possible then doctors keep a patient out of danger.The project presents a novel approach to brain tumor detection and also its classification at the same time.

This report presents a comprehensive framework for the detection and classification of brain tumors using advanced imaging techniques and deep learning algorithms. Our framework integrates magnetic resonance imaging (MRI) for precise anatomical visualization with deep learning models to enhance diagnostic accuracy. The core of the system involves a Convolutional Neural Network (CNN) trained on the diverse dataset of MRI images. We have used various CNN architectures and transfer learning to detect the brain tumors. The medical images of the brain are pre-processed followed by image segmentation. The relevant features are identified and extracted and the model is trained. The performance of model predicts whether tumor is present or not in image. This project marks a significant step towards bridging the gap between the power of deep learning models and the need for interpretable and trustworthy medical diagnostics.

[AH18]

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Chapter 1

Introduction

Brain tumor detection is a critical aspect of medical diagnostics, aiming to identify abnormal growths in the brain tissue. Artificial intelligence has demonstrated significant potential in increasing the precision and effectiveness of brain tumour identification. Utilizing advanced imaging techniques such as MRI and CT scans, healthcare professionals can pinpoint the location, size, and characteristics of tumors. This project deals with such a system that classifies the type of tumor using Convolution Neural Network (CNN) algorithm for MRI images of different patients. Detecting Brain tumor using Image Processing techniques involves the four stages is : Image Pre-Processing, Image segmentation, Feature Extraction, and Classification.

1.1 Brain Tumor Detection System

A brain tumor detection system is a medical imaging analysis system that uses artificial intelligence, machine learning and deep learning algorithms to detect and diagnose brain tumors from medical images such as MRI and CT scans. It is a complex, multidisciplinary approach that leverages advanced technologies to identify, classify and diagnose brain tumors accurately and efficiently. The main goal of such a system is to improve early detection, *enhance diagnostic accuracy, and assist in treatment planning. It also aims to assist medical practitioners in identifying the location, size, and type of tumors, which is essential for developing an effective treatment plan.*

1.1.1 Components

1. MEDICAL IMAGING TECHNIQUES :

- *Magnetic Resonance Imaging (MRI)*
- *Computed Tomography (CT) Scans*
- *Positron Emission Tomography (PET) Scans*
- *Ultrasound and X-ray*
- *Magneto Encephalo Graphy (MEG)*

2. IMAGE PROCESSING ANALYSIS :

- *Data acquisition*
- *Preprocessing*
- *Segmentation*
- *Feature extraction*
- *Classification*

3. COMPUTER-AIDED DIAGNOSIS (CAD):

- *Decision Support Systems*
- *Integration with Clinical Data*

1.2 Overview of the Brain

The human brain is the main part of our central nervous system and is responsible for regulating most bodily functions, including movement, sensation, thought, emotion, and homeostasis. It is a highly complex and organized structure made up of billions of neurons and glial cells. It is located in the human head and is covered by the skull.

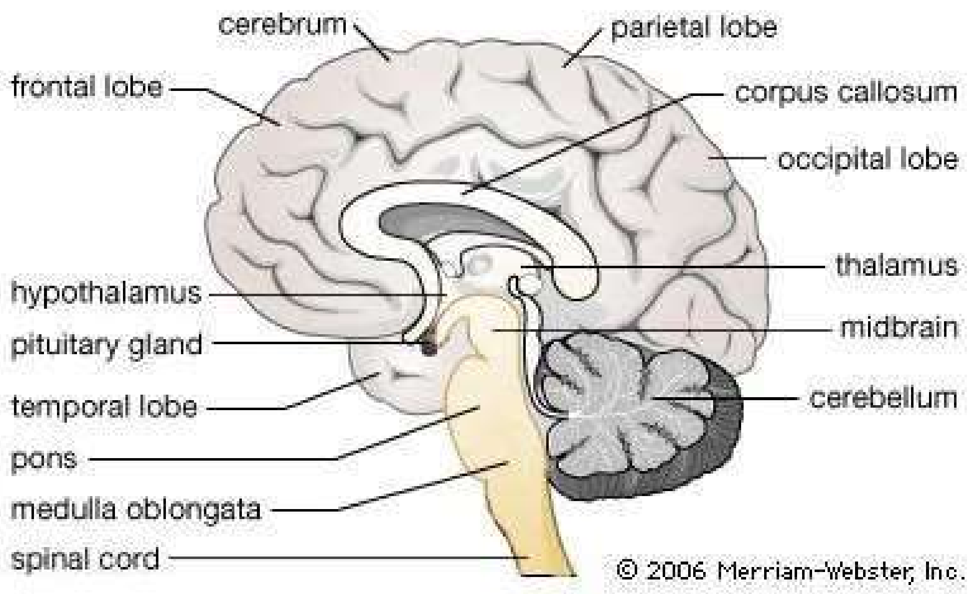

Fig. 1.1 Basic structure of human brain

Major parts of the brain are :-

1. *Cerebrum*
2. *Cerebellum*
3. *Brainstem*
4. *Limbic system*
5. *Diencephalon*
6. *Lobes : Frontal lobe, Parietal lobe, Temporal lobe, Occipital lobe*
7. *Hypothalamus*
8. *Pituitary gland*

1.3 Brain Tumors and its Types

Brain tumors are abnormal growths of cells within the brain or its surrounding tissues. These cells grow and multiply uncontrollably, seemingly unchecked by the mechanisms that control normal cells. Brain tumors range in size from very small to very large. Some brain tumors are found when they are very small because they cause symptoms that you notice right away. Other brain tumors grow very large before they're found.
They can be benign (non-cancerous) or malignant (cancerous).

Types of brain tumors

1. Primary brain tumors : *These tumors start in the brain or spinal cord and can be benign or malignant.*

- ***Originate :*** *In the brain or nearby tissues.*
- ***Common types :-***

  1. Gliomas **-** *Arise from glial cells. Subtypes include astrocytomas, oligodendrogliomas, and ependymomas.*

  2. Meningiomas **-** *Arise from the meninges, the protective membranes covering the brain and spinal cord.*

  3. Pituitary Adenomas **-** *Tumors that occur in the pituitary gland.*

  4. Schwannomas **-** *Arise from Schwann cells, typically affecting cranial nerves.*

2. Secondary (metastatic) brain tumors : *These tumors have spread to the brain from another part of the body. They are always cancerous and made up of the same type of cells as the primary cancer.*

- *Originate - From cancer cells that have spread from other parts of the body (e.g., lung, breast, kidney).*
- *Common types :-*
  1. *Lung cancer*
  2. *Breast cancer*
  3. *Kidney cancer*
  4. *Melanoma skin cancer*
  5. *Bowel (colorectal) cancer*
  6. *Thyroid gland cancer*

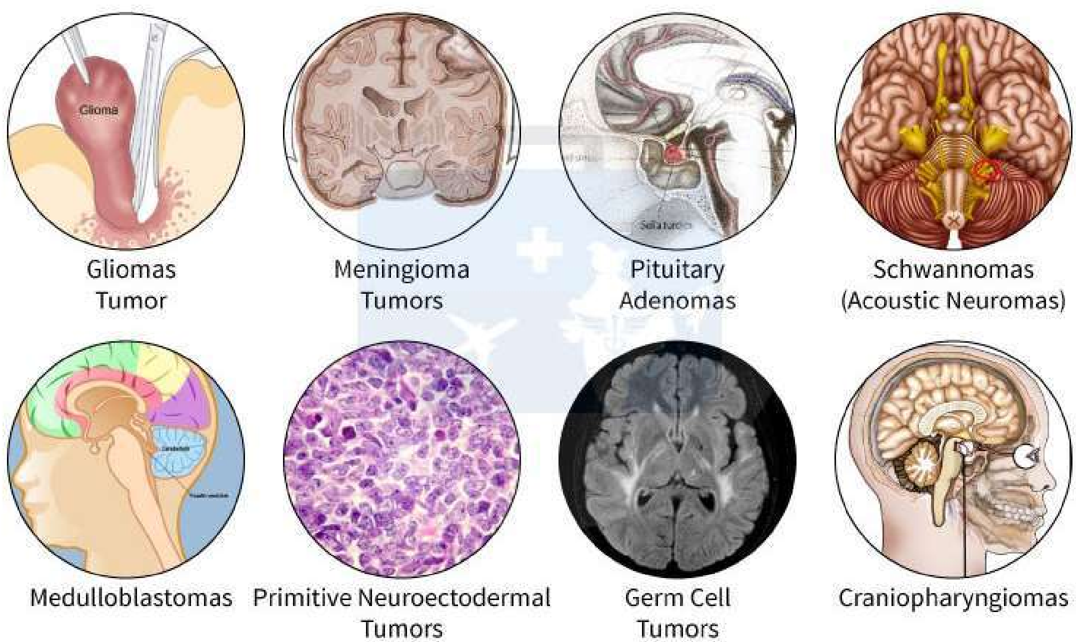

Fig. 1.2 Different types of brain tumors

[AH18]

1.4 Objectives

The main objectives of this system are :

1. Early Detection *- To identify brain tumors at an early stage and get timely intervention.*

2. Accurate Diagnosis *- To provide precise identification and characterization of brain tumors.*

3. Automated Segmentation *- To automate the process of tumor segmentation in medical imaging.*

4. Classification of Tumor Types *- To classify tumors into specific types and grades based on their characteristics.*

5. Integration with Clinical Data *- To combine imaging data with other clinical information (e.g., patient history, genetic data) for a comprehensive analysis.*

6. Enhancement of Radiologist and Oncologist Efficiency *- To provide decision support tools to assist healthcare professionals in diagnosing and planning treatment.*

7. Reduction of Diagnostic Costs *- To lower the overall costs associated with brain tumor diagnosis through automation and improved accuracy.*

8. Consistency and Standardization *- To ensure consistent and standardized diagnosis and classification across different healthcare facilities.*

9. Monitoring and Prognosis *- To track tumor progression and response to treatment over time.*

10. Research and Development *- To facilitate research by providing high-quality, annotated data for developing and testing new algorithms and treatment modalities.*

[RS19]

1.5 Motivation

The main motivation for developing and implementing a brain tumor detection and classification system is to not only detect tumor but it can also classify types of tumor. So it can be useful in cases such as we have to sure the tumor is positive or negative, it can detect tumor from image and return the result tumor is positive or not.

Here are the key motivations:

1. Improved Diagnostic Accuracy **-** *Traditional methods of diagnosing brain tumors can sometimes be inaccurate due to the complexity of brain structures and tumor heterogeneity.*

2. Reduction of Human Error **-** *Human error in interpreting medical images can lead to missed diagnoses or incorrect classifications.*

3. Cost-Effectiveness **-** *Traditional diagnostic processes can be time-consuming and expensive.*

4. Access to Advanced Diagnostics **-** *High-quality diagnostic resources may not be available in all healthcare settings, particularly in low-resource areas.*

5. Enhanced Efficiency for Healthcare Professionals **-** *Radiologists and oncologists face high workloads, which can lead to fatigue and decreased diagnostic accuracy.*

6. Support for Ongoing Research *- Understanding brain tumors is an ongoing research endeavor that requires large amounts of high-quality data.*

1.6 Applications

- *The main application of this system is tumor identification.*
- *Another main application is to classify the identified tumor as glioma, meningioma or pituitary.*
- *The main reason behind the development of this application is to provide proper treatment as soon as possible and protect the human life which is in danger.*
- *This application is helpful to doctors as well as patient*
- *The manual identification is not so fast, more accurate and efficient for user. It is user friendly application.*

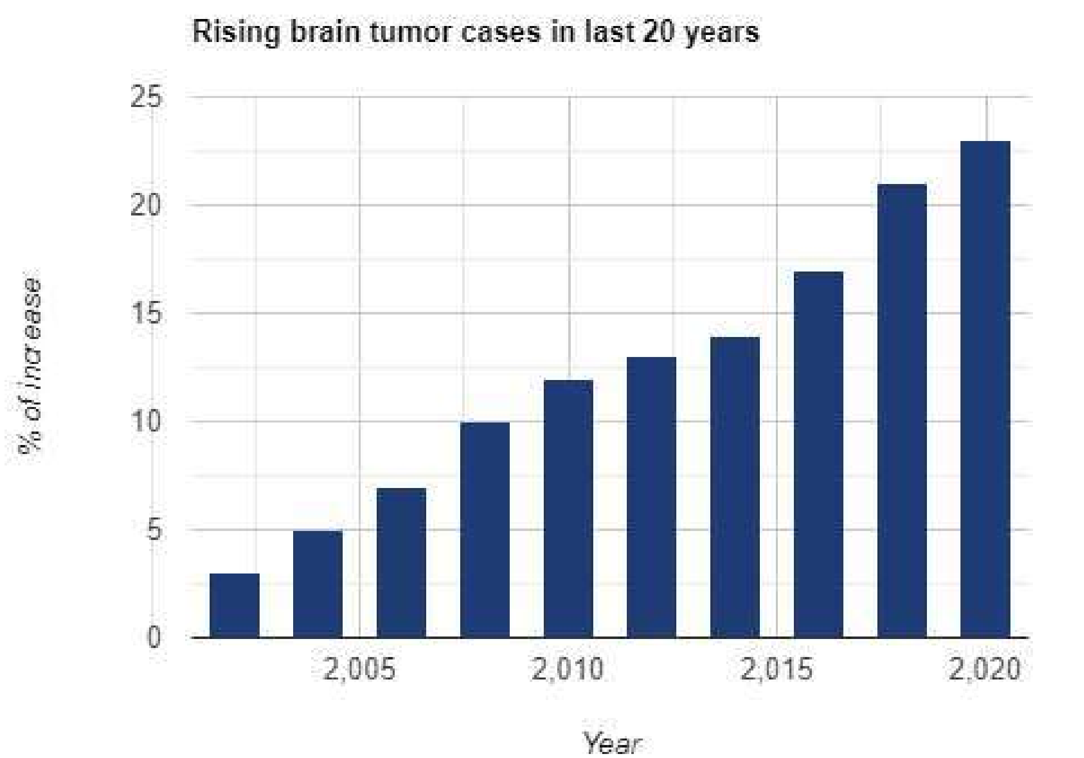

Fig. 1.3 Graph showing rising brain tumors

*The image in the previous page gives a graphical view of the rising cases of brain tumors in the last 20 years. Since the number of cases are increasing, there is a huge need of the "**Brain Tumor Detection & Classification System** developed for accurately and effectively predicting tumors.*

1.7 Organization of The Report

The project report is organized in the following manner :

Chapter 1 *i.e,* ***Introduction*** *gives the brief idea about the Brain Tumor Detection and Classification system.*

Chapter 2 *i.e,* ***Literature Survey*** *deals with surveys of prior research papers or journals on this particular topic.*

Chapter 3 *i.e,* ***Motivation and Plan of work****consists of the motivation and work plan of this system.*

Chapter 4 *i.e,* ***Details of the Databse*** *includes the complete information about the dataset used in our system.*

Chapter 5 *i.e,* ***Hardware and Software Requirements*** *discusses about the hardware and software required for developing the system.*

Chapter 6 *i.e,* ***Tools and Technologies used*** *gives insight to tools, technologies and environments required for deploying the system.*

Chapter 7 *i.e,* ***Improved methods*** *gives the details about some of the improved for brain tumor detection and classification system.*

Chapter 8 *i.e,* ***Execution of CNN*** *shows the entire implementation and experimental results of executing CNN in our system.*

Chapter 9 *i.e,* ***Execution of VGG-19 Architecture*** *shows the entire results after implementing VGG-19 in our system.*

Chapter 10 *i.e,* ***Execution by EfficientNetB3*** *consists of the results after implementing EfficientNetB3 in our system.*

Chapter 11 *i.e,* ***Execution by Yolo v8*** *contains the experimental results after implementing Yolo v8 algorithm in our system.*

Chapter 12 and 13 *i.e,* ***Conclusion and Future works*** *deals with the ultimate conclusion and future works of this project.*

[EVB+21]

Chapter 2

Literature Survey

Various research papers and literatures have been reviewed and surveyed in order to develop the project report. They are mentioned below :

Paper 1 : *Brain Tumor Detection : Model and Analysis*

Publication Year : *2022*

Author : *Abhiral Dubey, Atharva Pangerkar, Tejas Pawar, Santhosh Pillai, Prof.R.S. Bhoyar*

Journal Name : *International Journal of Innovative Research in Technology (IJIRT)*

Summary : *This research paper tries to impose that the brain tumor can be detected and classify into the respective tumor type by using the machine learning algorithms. The program will only be going to detect the MRI image as it is developed for it*

Paper 2 : *Brain Tumor Detection And Classification Using ML*

Publication Year : *2023*

Author : *Ashish Pimpalkar, Pranay Tembhurne, Amol Ingle, Vaibhav Gosawi, Pooja Patle*

Journal Name : *International Research Journal of Modernization in Engineering Tech-*

nology and Science (IRJMETS)

Summary : *This paper discusses how the features from the images have been extracted and utilized in machine learning models to improve tumor detection and classification accuracy.*

Paper 3 : *A Machine Learning based approach for Detection of Tumors*

Publication Year : *2021*

Author : *Kirankumar Madihalli, H R Ramya*

Journal Name : *Institute of Electrical and Electronics Engineers (IEEE)*

Summary : *The motive of the paper is to develop machine learning algorithms, which can detect the tumor without human interference and classify it as either cancerous tumor or non-cancerous tumor. Machine learning algorithms developed are logistic regression and fuzzy c means methods and then the results of both are compared.*

Paper 4 : *Classification of Brain Tumor types by Deep Learning with CNN*

Publication Year : *2019*

Authors : *Hasan Ucuzal, Şeyma YAŞAR, Cemil Çolak*

Journal Name : *Institute of Electrical and Electronics Engineers (IEEE)*

Summary : *his study aims to develop a free web-based software based on deep learning that can be utilized in the diagnosis and detection of brain tumors (Glioma/ Meningioma/ Pituitary) on T1-weighted magnetic resonance imaging.*

Paper 5 : *Development of a Novel Machine Learning Framework for Brain Tumors*

Publication Year : *2023*

Authors : *Rashi Bhave, Yati Kale, Yuvraj Khare, Dr. Sharmishta Desai*

Journal Name : *International Journal of Engineering Research Technology (IJERT)*

Summary : *This research paper deals with a proposed model which was able to achieve an accuracy of 83.1 percent in predicting different types of tumors in MRI images.*

Paper 6 : *Explainable-AI Based Model for Brain Tumor Detection*

Publication Year : *2023*

Authors : *Aditya Sinha, Rahul Rai, Ankit Kumar, Sindhu Kumari Varma, Snigdha Sen*

Journal Name : *International Journal of Advanced Research in Computer and Communication Engineering (IJARCCE)*

Summary : *The study addresses the critical need for transparency and interpretability in AI-based medical diagnostics. The paper concludes with insights into the future development and applications of XAI in medical imaging for brain tumor detection.*

Paper 7 : *Brain Tumor Segmentation in MRI Images*

Publication Year : *2019*

Authors : *Adarsh Dhiman, Prof. B.S. Satpute*

Journal Name : *International Journal of Research in Advent Technology (IJRAT)*

Summary : *This paper prescribes to utilize Convolutional Neural Network based deep learning methods to segment the MRI image. The progress in image segmentation methods will incredibly aid in automated identification of tumor.*

2.1 Overview of Existing Work

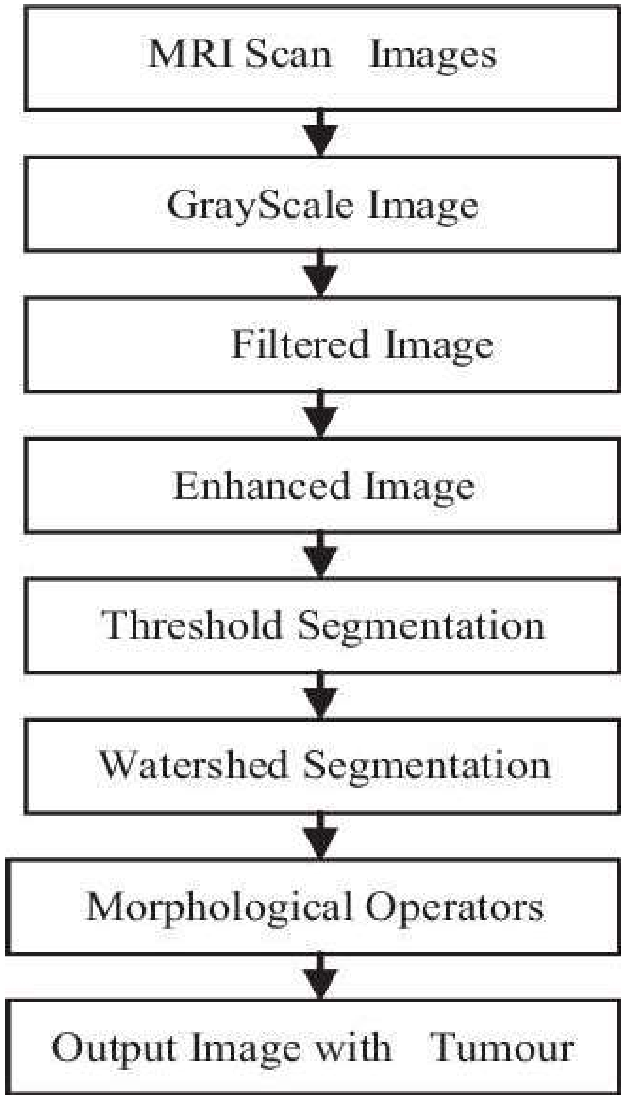

Fig. 2.1 Existing work flow of brain tumor detection

Existing methods of brain tumor detection and classification systems involve some of the old algorithms and not the advanced Machine Learning and Deep Learning algorithm. Among the old techniques, some of them include the threshold segmenting methods, watershed segmentation, morphological operations, etc.

[DSS21]

- ***1st stage :*** *There is a computer based procedures to detect tumor blocks and classify the type of tumor using Artificial Neural Network Algorithm for MRI images of different patients.*

- ***2nd stage :*** *This stage involves the use of different image processing techniques such as histogram equalization, image segmentation, image enhancement, morphological operations and feature extraction for brain tumor detection in the MRI images for the cancer-affected patients.*

- *This work has introduced one automatic brain tumor detection method to increase the accuracy and decrease the diagnosis time.*

- ***Image preprocessing*** ***:*** *Using high pass filter, noise in the images are removed.*

- ***Segmentation*** ***:*** *Region growing and pixel based image segmentation techniques are used.*

- ***Morphological operation*** ***:*** *It is used for the extraction of boundary areas of the brain images.*

- ***Feature extraction*** ***:*** *This is used for edge detection of the images*

- ***Connected component labeling*** ***:*** *Every set of connected pixels having same gray-level values are assigned the same unique region label*

- ***Tumor identification*** ***:*** *In this phase, tumors from the brain MRI images are identified.*

2.2 Notable Contributions

- *Cheng et al. (2016) : Developed a CNN-based framework for both segmentation and classification of brain tumors, demonstrating improved performance over traditional methods.*

- *Akkus et al. (2017): Reviewed the application of deep learning in brain MRI analysis, highlighting advancements and challenges in the field.*

- *Hosseini-Asl et al. (2018) : Developed a deep residual learning approach specifically for brain tumor classification, achieving high accuracy and robustness.*

- *Zhang et al. (2019) : Proposed a multi-modal deep learning approach combining MRI and genomic data for the classification of glioblastoma subtypes.*

[BNK15]

Chapter 3

Motivation and Plan of Work

Motivation :

The main motivation behind Brain tumor detection is to not only detect tumor but it can also classify types of tumor. Following are some of the motivations :-

1. *High Prevalence and Severity of Brain Tumors*
2. *Challenges in Manual Diagnosis*
3. *Technological Advancements in Deep Learning*
4. *Improved Diagnostic Accuracy and Speed*
5. *Accessibility to Quality Healthcare*
6. *Class-Specific Treatment Plans*
7. *Potential to Reduce Healthcare Costs*
8. *Enhancing Research and Development*

3.1 Detailed Methodology

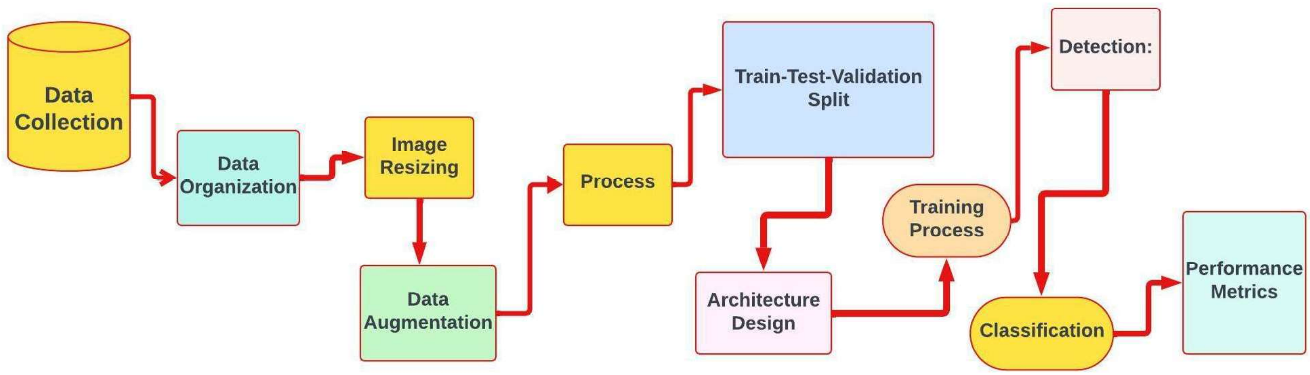

Fig. 3.1 Methodology of the system

1. ***Dataset (Brain MRI Images)***
   - ***Data collection :*** *Collection of MRI images from reputable sources such as medical image repositories, datasets available online, etc.*
   - ***Data Organization :*** *Organizing the dataset into separate folders for training, validation, and testing sets, with subfolders for each class.*
2. ***Pre-processing***
   - ***Image Resizing :*** *Resizing of all images to a consistent size. This is essential for feeding images into neural networks.*
   - ***Normalization :*** *Normalization of pixel values to a common range (e.g., [0, 1] or [-1, 1]). This speeds up convergence during training by ensuring that all input features are on a similar scale.*
   - ***Data Augmentation :*** *Augmentation of the data to artificially increase the dataset size and variability, thereby improving model generalization and robustness.*
3. ***Split the Data***

- ***Train-Test Split*** **:***Splitting the dataset into training and testing sets using an 80-20 or 70-30 ratio.*

- ***Validation Split*** **:***Further splitting the training set into training and validation subsets, usually with an 80-20 ratio.*

4. ***Model Deployment***

- ***Custom CNN Algorithm*** **:** *Has layers like convolutional layers, pooling layers, fully-connected layers (dense), flatten layer and dropout layer.*

- ***VGG 19*** **:** *It is a pre-trained transfer learning model which has already learned useful features from a large dataset.*

- ***EfficientNet*** **:** *EfficientNet models are designed to optimize accuracy and efficiency by scaling depth, width, and resolution systematically.*

- ***YOLO V8*** **:** *YOLO (You Only Look Once) models are designed for real-time object detection, identifying and localizing multiple objects in an image.*

5. ***Detection and Classification***

- ***ROI Extraction*** **:** *For models like YOLO V8, detect regions of interest (ROIs) in the MRI images where tumors are likely present.*

- ***Localization*** **:** *YOLO provides bounding boxes around detected objects, allowing for precise localization of tumors.*

- ***CNN Classification*** **:** *YOLO provides bounding boxes around detected objects, allowing for precise localization of tumors.*

- ***Ensemble Methods*** **:** *It combines predictions from multiple models to improve accuracy and robustness.*

6. ***Performance metrics***

- ***Accuracy* :** *Measure of the percentage of correctly classified instances out of the total instances.*
- ***Precision & Recall* :** *Precision indicates the accuracy of positive predictions, while recall indicates the model's ability to identify all positive instances.*
- ***F1-score* : *The harmonic mean of precision and recall, providing a balanced measure of model performance.***
- ***Confusion matrix*** *: A detailed table showing true positives, true negatives, false positives, and false negatives for each class, helping to diagnose classification errors.*

[SANI16]

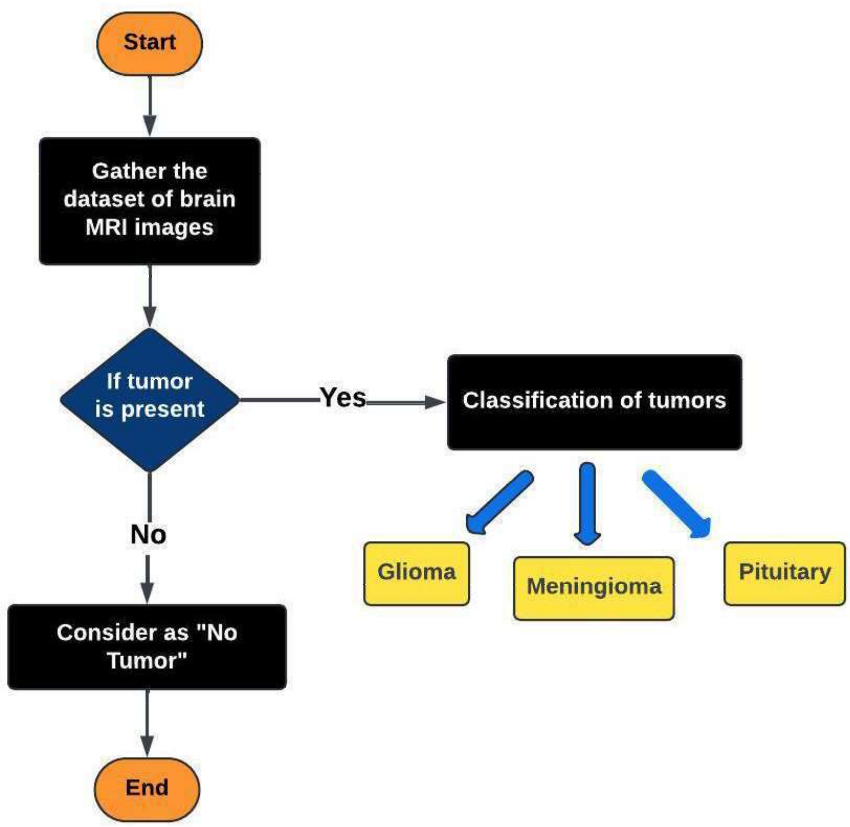

Fig. 3.2 Flowchart of the proposed system

3.2 Proposed Workflow

This system contains 5 basic working modules. The proposed workflow

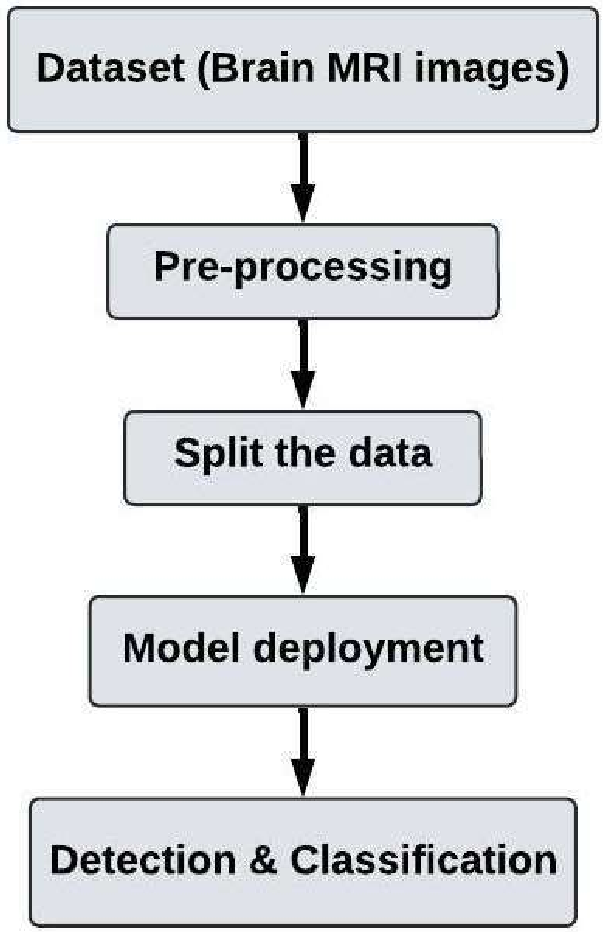

Fig. 3.3 General workflow of brain tumor detection and classification system

The proposed system mainly has 5 modules - Data acquisition (dataset i.e, brain MRI images), data preprocessing, data splitting, model deployment and finally detection and classification. These five working modules are further divided into detailed steps which are explained further in the report.

1.<u>Data Acquisition</u> - *This is the initial stage of the entire system. Here, a large dataset of brain MRI or CT scans from medical databases or hospitals are collected.*

2.<u>Data preprocessing</u> - *image cleaning, label encoding and data augmentation*

1. *Noise reduction*
2. *Feature extraction*
3. *Normalization*
4. *Augmentation*

3.<u>Splitting the dataset</u> - *the entire dataset is classified into 3 segments :-*

1. *Training data*
2. *Validation data*
3. *Testing data*

3.<u>Model deployment</u> - *developing different algorithms on the training data to produce comparitable results. The algorithms used are :-*

1. *CNN*
2. *VGG-19*
3. *EfficientNet b3*
4. *Yolo v8*

3.<u>Detection and Classification</u> - *The images are tested on the algorithm, detected and classified into the 3 types of tumors.*

3.3 General Working of CNN

- *A Convolutional Neural Network (CNN) is a type of Deep Learning neural network architecture commonly used in Computer Vision.*
- *Convolutional Neural Networks use three-dimensional data for image classification and object recognition tasks.*
- *It is the extended version of artificial neural networks (ANN) which is predominantly used to extract the feature from the grid-like matrix dataset.*
- *It contains multiple layers like the input layer, Convolutional layer, Pooling layer, and fully connected layers.*

[KPSP20]

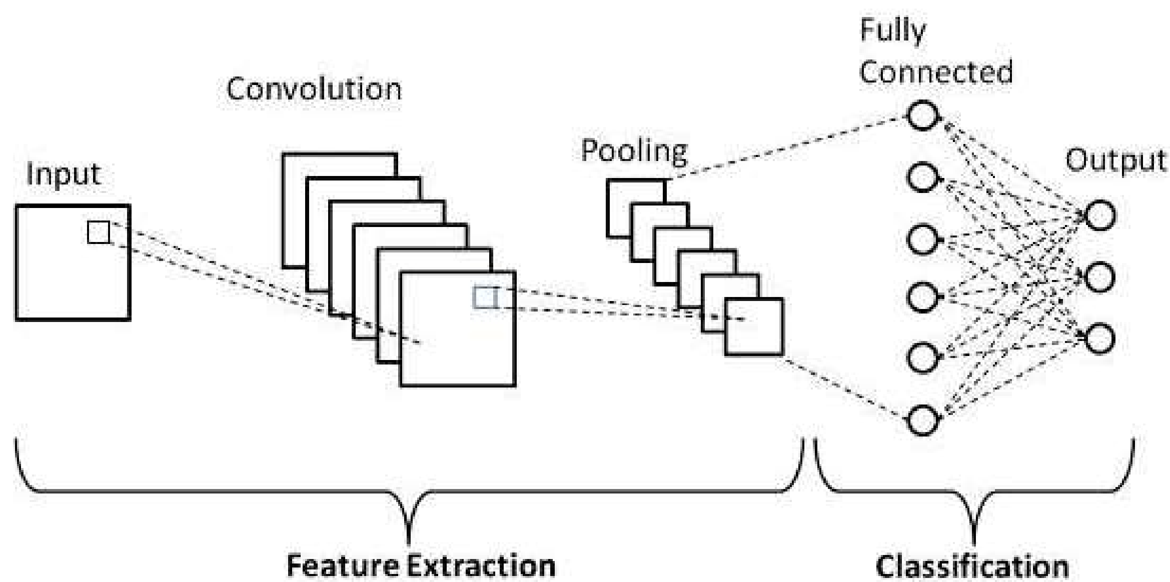

Fig. 3.4 Basic CNN model

3.3.1 Structure of CNN

1. ***Input Layer :*** *The input layer receives the raw pixel values of the image. Typically, for a color image, this would be a three-dimensional array.*

2. ***Convolutional Layers :*** *These are the core building blocks of a CNN. They apply convolution operations to the input, using a set of filters (or kernels) to extract features from the input image.*

3. ***Pooling Layers :*** *These layers reduce the spatial dimensions (height and width) of the feature maps, which helps in reducing the computational load and controlling overfitting.*

4. ***Fully Connected (Dense) Layers :*** *In these layers, each neuron is connected to every neuron in the previous layer. The output from the final pooling or convolutional layer is flattened into a one-dimensional vector before being fed into the fully connected layers.*

5. ***Output Layer :*** *The final layer of the CNN is the output layer, which typically uses a softmax activation function for classification tasks. This layer outputs a probability distribution over the possible classes.*

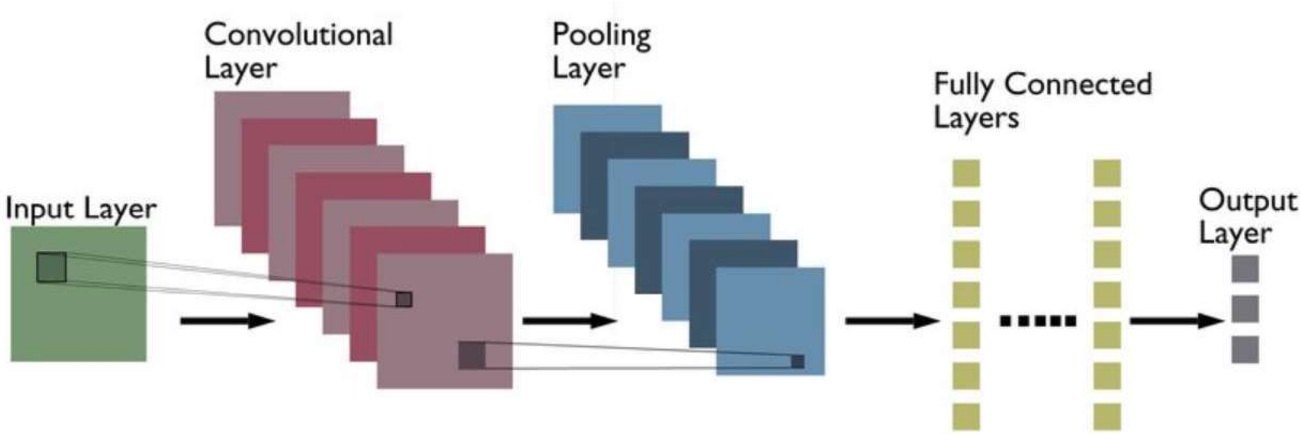

Fig. 3.5 Structure of CNN

3.3.2 Working of a CNN Step-by-Step

1. ***Convolution operation*** **:** *The input image is convolved with multiple filters to produce feature maps. These filters detect various features such as edges, corners, and textures.*

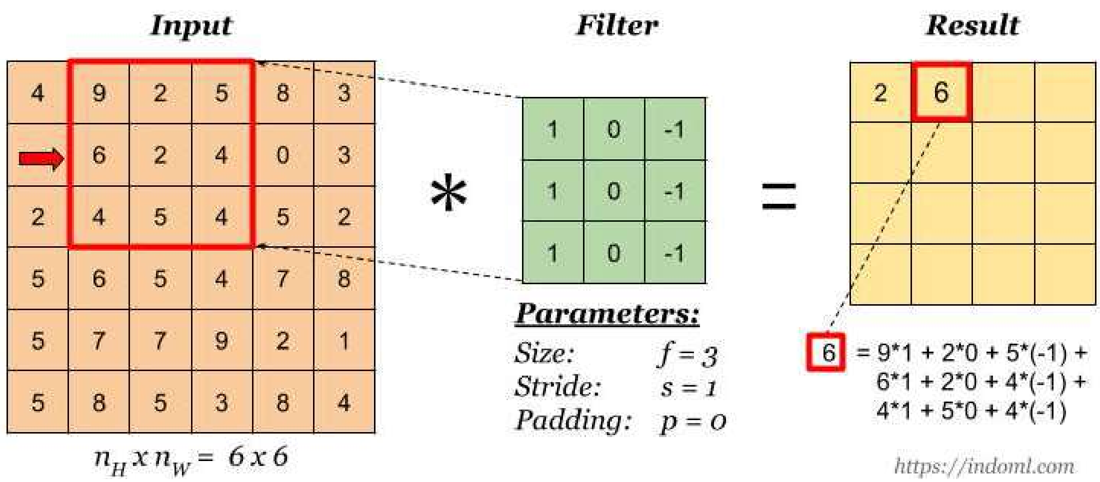

Fig. 3.6 Sample convolution operation

2. ***Non-Linearity (ReLU)*** **:** *The feature maps are passed through the ReLU activation function to add non-linearity to the model, allowing it to learn complex patterns.*

3. ***Pooling*** **:** *The feature maps are downsampled using pooling layers. This reduces the dimensions of the feature maps while retaining the most important features.*

4. ***Stacking Convolutional and Pooling Layers*** **:** *Multiple convolutional and pooling layers are stacked to progressively learn higher-level features. Early layers might detect simple edges, while deeper layers detect more complex structures like objects or faces.*

5. ***Flattening*** **:** *The output of the last pooling layer is flattened into a single long vector, which serves as the input to the fully connected layers.*

6. ***Fully Connected Layers*** **:** *These layers perform the final high-level reasoning. They learn to combine the features extracted by the convolutional layers to make a*

final prediction.

7. ***Fully Connected Layers :*** *The final output layer produces a probability distribution over the classes.*

[RV18]

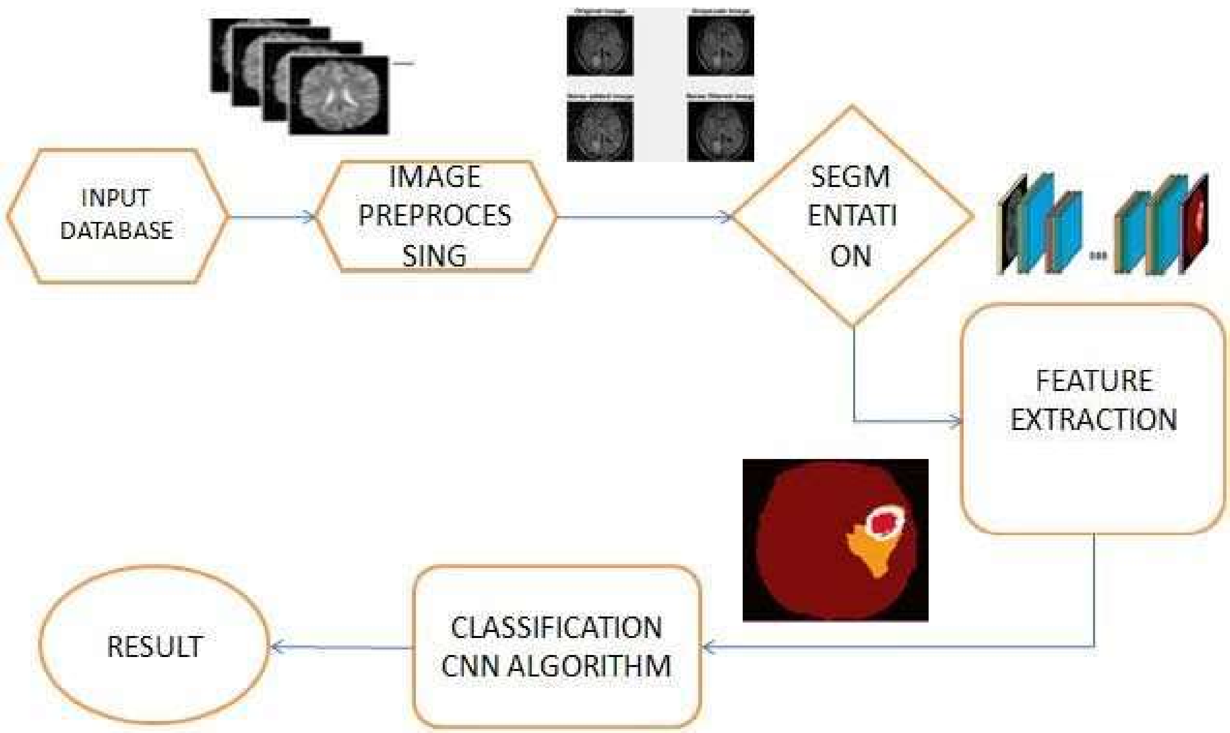

Fig. 3.7 Working of CNN

Few terms used in CNN :-

Padding : *This means adding extra pixels around the input before doing operations.*

Filter/kernel : *It is a small matrix of weights that slides over the input data (such as an image), performs element-wise multiplication with the part of the input it is currently on, and then sums up all the results into a single output pixel.*

Stride : *It determines how many squares or pixels our filters skip when they move across the image, from left to right and from top to bottom.*

3.4 Concept of Transfer Learning

- *Transfer learning is a machine learning technique where a model developed for a particular task is reused as the starting point for a model on a second task.*

- *It leverages the knowledge gained from a pre-trained model on a large dataset to solve a new, related problem with a smaller dataset.*

- *his approach is especially useful in deep learning where models are trained on vast amounts of data and require substantial computational resources.*

It consists of the following :-

1. *Pre-trained models*

2. *Feature extraction*

3. *Fine tuning*

Examples of transfer learning models are :- ***VGG-16, VGG-19, ResNet, ElasticNet, EfficientNet*** *etc.*

[SGK15]

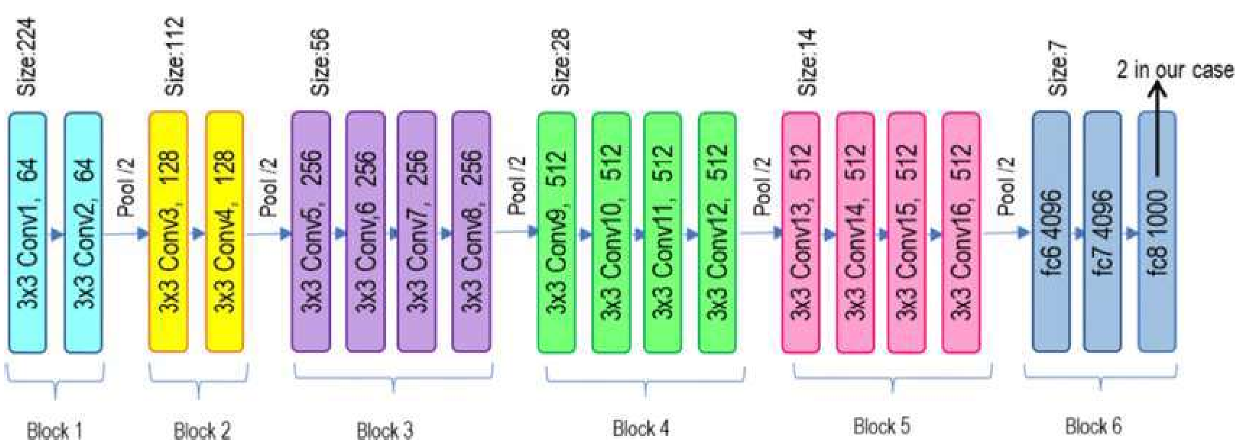

Fig. 3.8 Sample transfer learning model

3.5 General working of VGG-19

- *VGG-19 is a convolutional neural network (CNN) architecture that was introduced in 2014 by Simonyan and Zisserman in their paper "Very Deep Convolutional Networks for Large-Scale Image Recognition".*
- *t is a variant of the VGG (Visual Geometry Group) family of models, which are known for their simplicity and effectiveness in image classification tasks.*
- *VGG-19 consists of 19 layers, including 16 convolutional layers and 3 fully connected layers.*

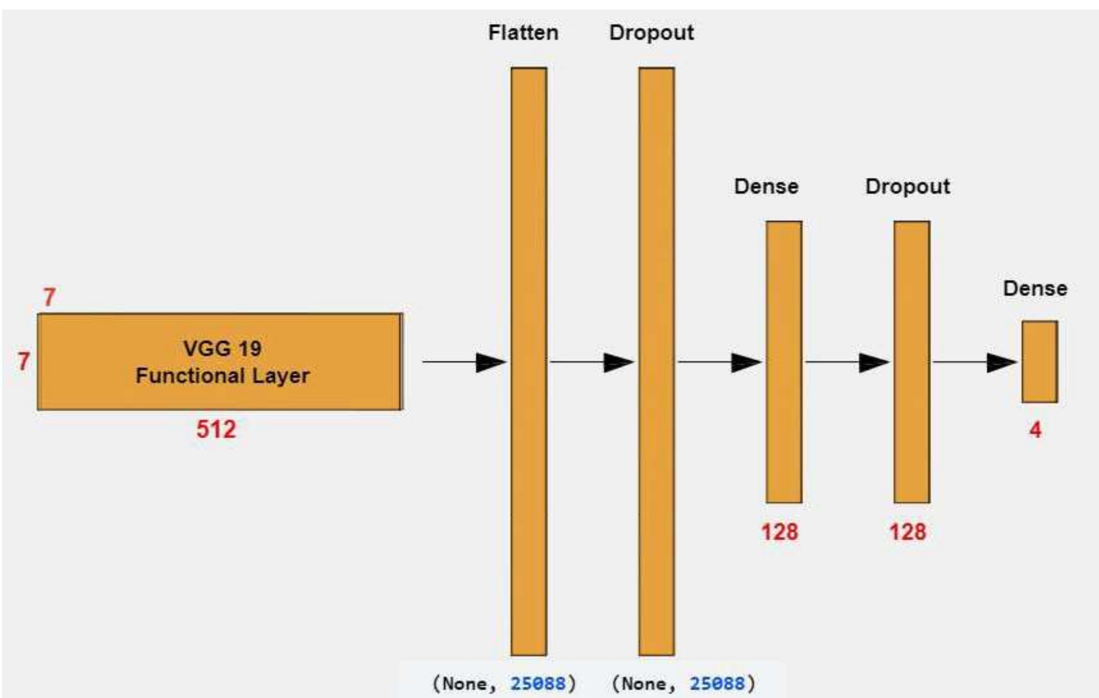

Fig. 3.9 Basic VGG-19 architecture

FEATURES :-

1. VGG-19 is a deep network with 19 layers, which allows it to learn complex features from images.

2. The architecture of VGG-19 is relatively simple, with a focus on convolutional and pooling layers.

3. VGG-19 has a large number of parameters, which allows it to learn rich feature representations from images.

3.5.1 Structure of VGG-19

The architecture can be broken down into the following components:

1. ***Convolutional layers :*** *The model starts with a series of convolutional layers, each followed by a ReLU (Rectified Linear Unit) activation function and a max pooling layer. The convolutional layers have a filter size of 3x3.*

2. ***Max Pooling layers :*** *The max pooling layers have a stride of 2 and a pool size of 2x2, which reduces the spatial dimensions of the feature maps.*

3. ***Fully Connected layers :*** *The output of the convolutional and pooling layers is flattened and fed into three fully connected layers.*

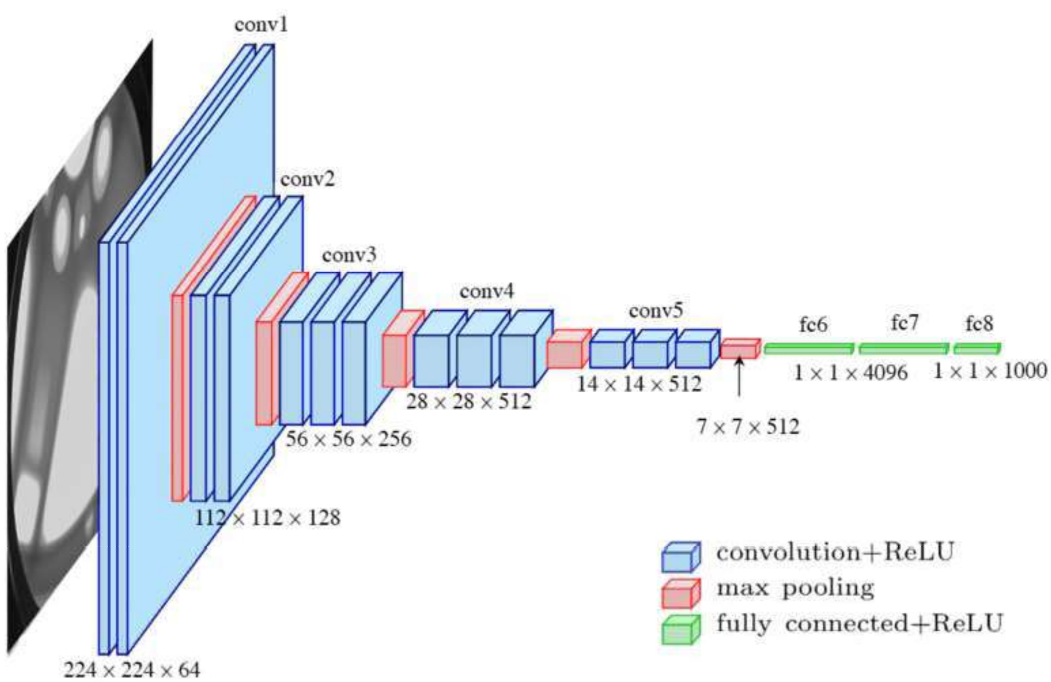

Fig. 3.10 Structure of VGG-19

3.5.2 Step-by-step Working of CNN

The working steps of the VGG-19 model can be broken down into the following stages :-

- *The model trains throughout many epochs by taking one forward and one backward pass of all training samples each time.*
- *Forward propagation calculates the loss and cost functions by comparing the difference between the actual and predicted target for each labeled image.*
- *Backward propagation uses gradient descent to update the weights and bias for each neuron, attributing more impact on the neurons.*
- *As the model sees more examples, it learns to better predict the target causing the loss measure to decrease.*
- *The cost function takes the average loss across all samples indicating overall performance.*

[ÖSA20]

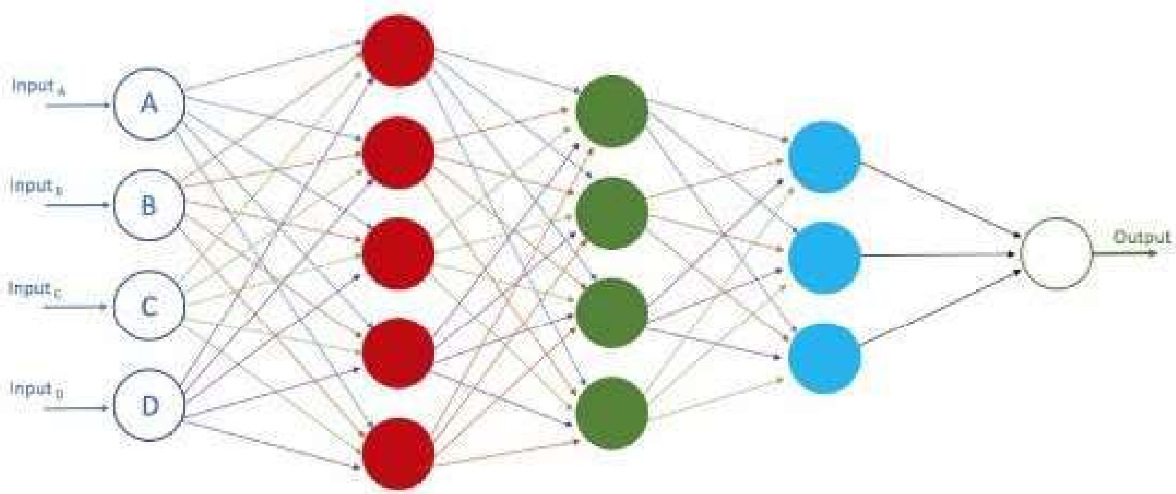

Fig. 3.11 Working of VGG-19 network

[SSK+20]

3.6 Description of EfficientNet B3

- *EfficientNet is a family of convolutional neural networks (CNNs) developed by Google.*
- *It aims to achieve higher accuracy and efficiency by optimizing the model scaling process.*
- *EfficientNet B3 is the fourth model in the series, with increasing complexity and performance from B0 to B7.*
- *These models are based on a compound scaling method that uniformly scales the depth, width, and resolution of the network to achieve better performance.*
- *EfficientNet B3 strikes a balance between accuracy and efficiency, making it suitable for various computer vision tasks.*

[CLR14]

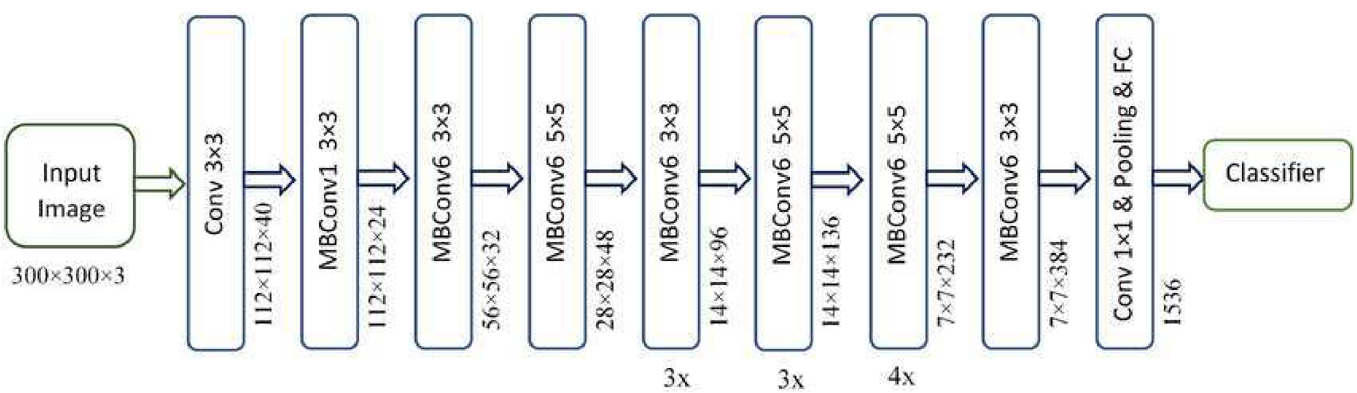

Fig. 3.12 Schematic representation of EfficientNet B3

Reasone to use EfficientNet B3 : *EfficientNet's strength lies in its ability to achieve high accuracy while maintaining efficiency. This makes it an important tool in scenarios where computational resources are limited.*

3.6.1 Structure of EfficientNet B3

The architecture of the EfficientNet B3 includes the following :-

1. ***MBConv Blocks* :** *EfficientNet uses Mobile Inverted Bottleneck Convolution (MBConv) blocks with depthwise separable convolutions, which reduce computational complexity and parameters while maintaining performance.*

2. ***Squeeze-and-Excitation (SE) Layers* :** *SE layers adaptively recalibrate channel-wise feature responses by modeling interdependencies between channels, enhancing feature representation.*

3. ***Depthwise Separable Convolutions* :** *Separate spatial convolution (depthwise) and pointwise convolution (1x1 convolution).*

4. ***Expansion and Projection* :** *The block starts with an expansion phase, increasing the number of channels, followed by depthwise convolution and then a projection phase, reducing the channels back to the original number.*

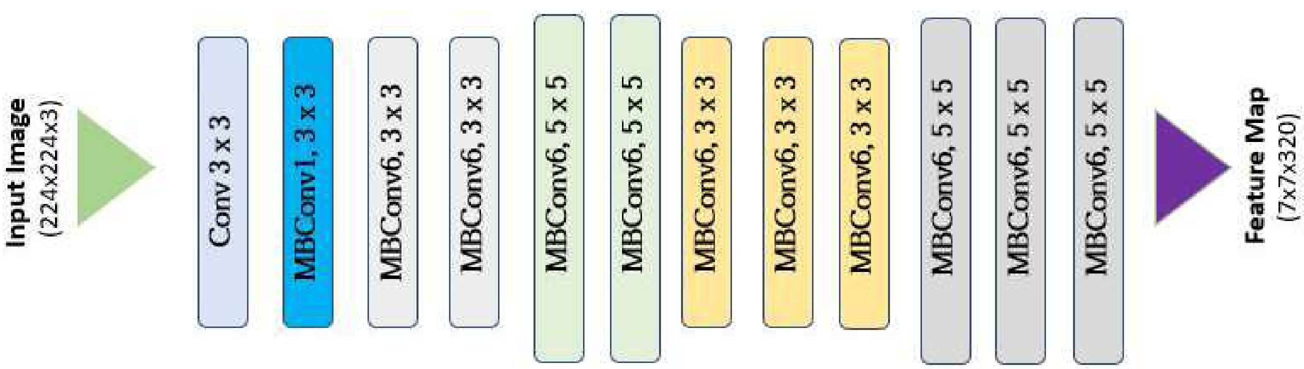

Fig. 3.13 Architecture of EfficientNet B3

3.6.2 Working of EfficientNet B3

1. ***Input Image Processing*** **:** *The input image is resized and pixel values are normalized to match the pretraining conditions.*

2. ***MBConv Blocks*** **:** *Each stage consists of multiple MBConv blocks with increasing depth and width to capture hierarchical features and to progressively extract features at various scales and depths.*

3. ***Feature Extraction and Downsampling*** **:** *The network employs depthwise separable convolutions for efficient feature extraction and downsampling through strides and pooling.*

4. ***Output*** **:** *The final layer is a softmax layer that outputs probabilities for classes.*

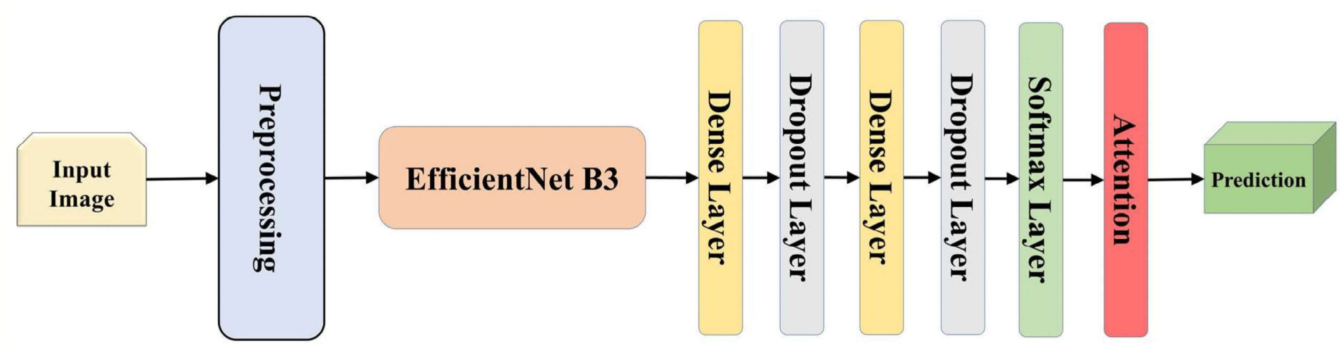

Fig. 3.14 Working of EfficientNet B3

3.7 Overview of YOLO v8

- *YOLOv8 is the latest iteration of the "You Only Look Once" (YOLO) family of models designed for real-time object detection developed by Ultralytics.*
- *The YOLOv8 model is designed to be fast, accurate, and easy to use, making it an excellent choice for a wide range of object detection and image segmentation tasks.*
- *It can be trained on large datasets and is capable of running on a variety of hardware platforms, from CPUs to GPUs.*

3.7.1 Key features

1. *Speed and Efficiency*
2. *Improved Accuracy*
3. *Scalability*
4. *Flexibility*

3.7.2 General working

1. Input processing : *The input to YOLOv8 is an image, typically resized to a fixed size, normalized and passed through the network.*

2. Feature Extraction (Backbone) : *The backbone of YOLOv8 processes the input image to extract hierarchical features.*

3. Feature Aggregation (Neck) : *The neck of the network aggregates features from different layers to create multi-scale feature maps. This helps in detecting objects of various sizes more effectively.*

4. Prediction (Detection Head) :*The detection head uses the aggregated features to predict bounding boxes, class probabilities, and confidence scores for objects in the image.*

5. Post-Processing : *Non-Maximum Suppression (NMS) is applied to remove duplicate* *detections and keep the best bounding box for each object. This step ensures that the model outputs one bounding box per detected object.*

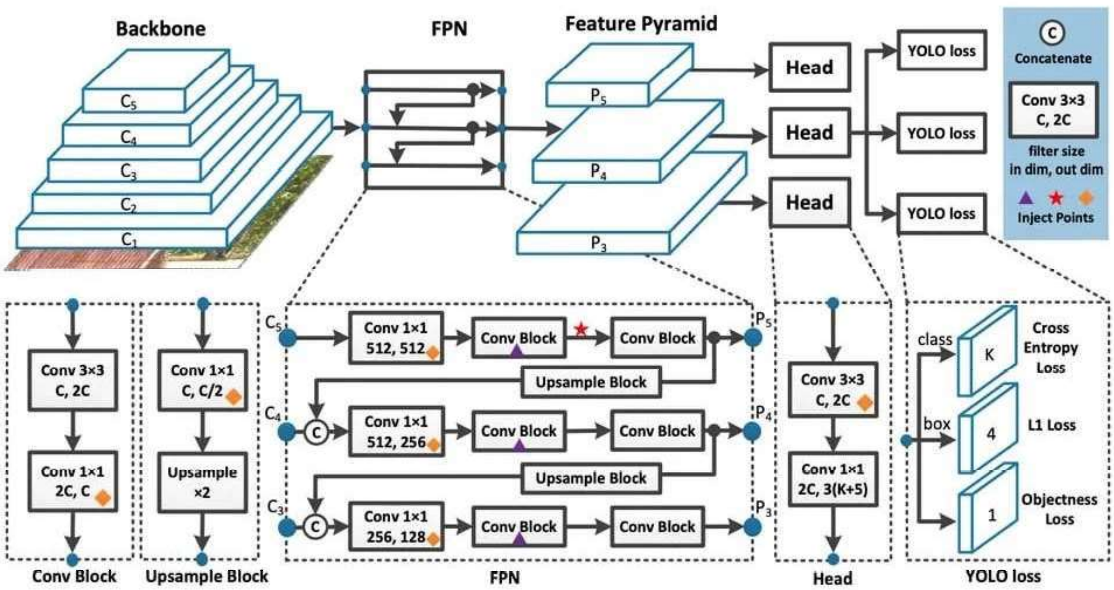

Fig. 3.15 Structure of Yolo v8

[RPSM21]

Chapter 4

Details of the Database

The dataset used in the project is a collection of MRI images of the human brain.

The complete details of the used dataset is specified below :-

- ***Total number of images*** *: 7023*

The dataset is further classified into two folders :- ***Training and Testing***

The training and testing folders have 4 class each. They are :-

- ***Glioma, Meningioma, No tumor and Pituitarty***

- ***Source of the dataset*** *: Kaggle*

- *The dataset is a combination of the following three datasets :*

  figshare, SARTAJ dataset, Br35H

- *The dataset is divided in the following manner :-*

  Training set - 81.3%

  Validation set - 9.3%

  Testing set - 9.4%

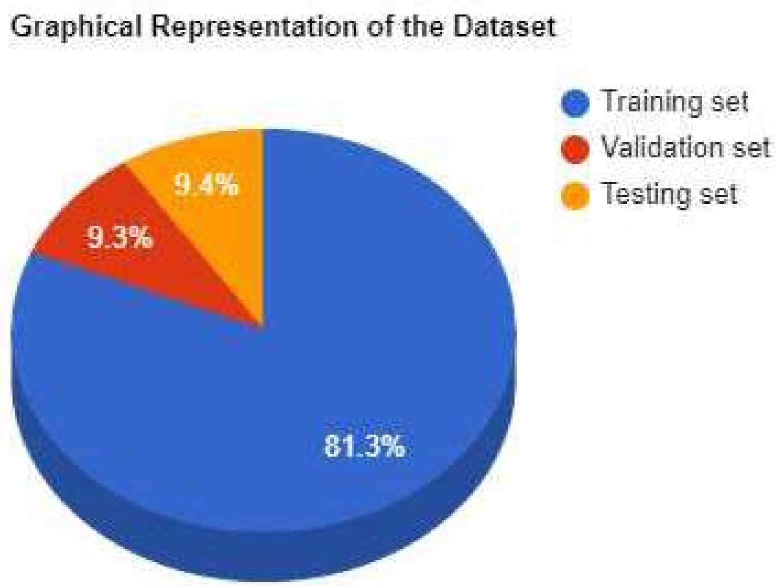

Fig. 4.1 Division of the Dataset

4.1 About training data

- ***Purpose*** **:** *The training data used in our system helps in training the model by learning patterns, relationships, and features within the data.*
- ***Size*** **:** *The training data occupies the largest portion to ensure that the model has enough examples to learn from and generalize well to new and unseen data.*
- ***Importance*** **:** *The quality and quantity of training data significantly impact the model's performance.*

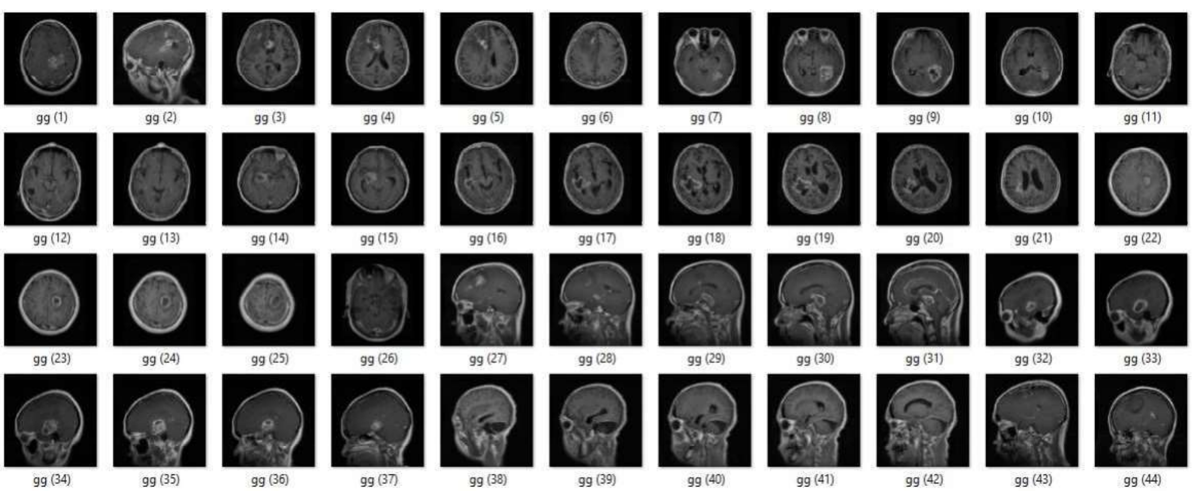

Fig. 4.2 Few training data from the dataset

4.2 About validation data

- ***Purpose*** **:** *The validation data used in our system helps in tuning the hyper-parameters and make decisions about model architecture.*
- ***Size*** **:** *The validation data is smaller than the training set but large enough to provide a reliable estimate of model performance. It acts as a proxy for the test set during model development.*
- ***Importance*** **:** *It prevents overfitting to the training data by ensuring that model improvements generalize beyond the training set.*

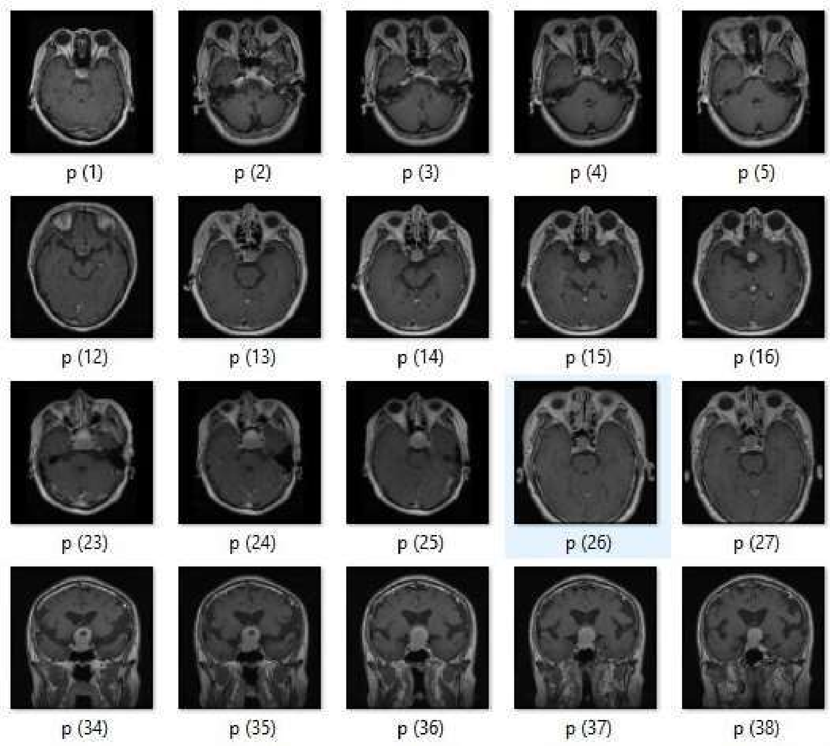

Fig. 4.3 Few validation data from the dataset

4.3 About testing data

- ***Purpose*** **:** *The testing data used in our system helps evaluate the final model's performance and provide an unbiased assessment of how the model will perform on completely new data.*

- ***Size*** **:** *The validation data occupies the smallest portion because it's only needed to give a final estimate of the model's generalization performance after all training and hyperparameter tuning are complete.*

- ***Importance*** **:** *It Provides a final, unbiased evaluation metric to compare different models or approaches objectively.*

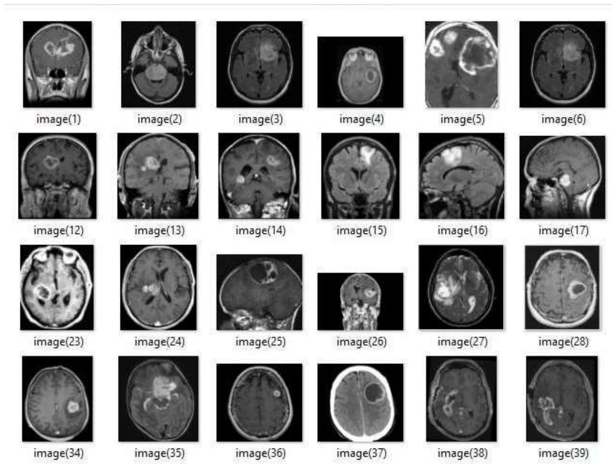

Fig. 4.4 Few testing data from the dataset

Our dataset contains brain MRI images in 3 different views :- ***axial, coronal and sagittal***

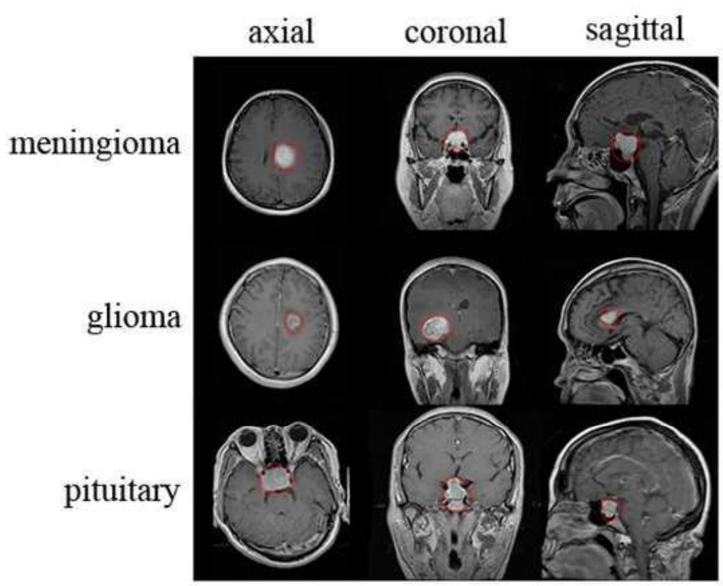

Fig. 4.5 Different views of brain in the dataset

Chapter 5

Hardware and Software Requirements

Implementing a brain tumor detection and classification system using CNN, VGG19, EfficientNet B3 and Yolo v8 involves both hardware and software requirements to ensure efficient processing, model training, and deployment.
Given below are some of the reasons for hardware requirements :-

- ***Computational power :*** *Provides the physical infrastructure necessary to execute software instructions, perform calculations, and store data.*
- ***Performance :*** *Determines the speed and efficiency with which tasks can be completed. High-performance hardware can handle more complex computations and larger datasets.*
- ***Input/Output Operations :*** *Facilitates interaction with the system through input devices (e.g., keyboards, mice, sensors) and output devices (e.g., monitors, printers, actuators).*

Given below are some of the reasons for software requiremnets :-

- ***Functionality*** **:** *Provides the instructions and algorithms that direct hardware to perform specific tasks. Defines what the project does and how it does it.*

- ***User Interface*** **:** *Allows users to interact with the hardware in an intuitive and effective manner.*

- ***Development and Management*** **:** *Tools and environments required to develop, test, deploy, and maintain the project. Includes compilers, development environments, version control systems, and deployment platforms.*

5.1 Hardware requirements

- ***CPU :*** *Multi-core processor (Intel i5/i7/i9, AMD Ryzen 7/9, or higher)*

- ***GPU :*** *Dedicated GPU with CUDA support for accelerated deep learning (NVIDIA GTX 1080 Ti, P100, RTX 2080, RTX 3080, or higher)*

- ***RAM :*** *At least 16GB, preferably 32GB or more*

- ***Storage :*** *SSD (512GB or more) for faster data access and model training*

5.2 Software requirements

- ***Operating system :*** *Windows 10/11, mac OS or Ubuntu*

- ***Programming language :*** *Python 3.7 or higher*

- ***Development environment :*** *Kaggle, Google colab*

Chapter 6

Tools and Technologies used

To implement a Brain Tumor Detection and Classification system using different algorithms like CNN, VGG19, EfficientNet B3 and Yolo v8 a variety of tools and technologies are employed. These tools span across different stages of the project, from data collection and preprocessing to model training, evaluation, and deployment.

6.1 Programming Language used

Python was the language of selection for this project.

This was a straight-forward call for the following reasons :-

- *It is a versatile programming language widely used in data science and machine learning.*
- *Python as a language has a vast community behind it. Any problems which may be faced is simply resolved with a visit to Stack Overflow.*
- *Python has an abundance of powerful tools prepared for scientific computing packages like NumPy, Pandas and SciPy area unit freely available and well documented. Packages like these will dramatically scale back, and change the code required to write a given program.This makes iteration fast.*

- *Python as a language is forgiving and permits for program that appear as if pseudo code. This can be helpful once pseudo code given in tutorial papers must be enforced and tested. Using python this step is sometimes fairly trivial.*

6.2 Libraries used

- ***Numpy :*** *For numerical computations and handling arrays*
- ***Pandas :*** *For data manipulation and analysis*
- ***Matplotlib :*** *For creating static, animated, and interactive visualizations in Python.*
- ***Seaborn :*** *For statistical data visualization, built on top of Matplotlib.*
- ***Scikit-learn :*** *Used for training the classifier and evaluating its performance*

6.3 Deep Learning Frameworks used

- ***Tensorflow :*** *An open-source deep learning framework developed by Google, used for creating and training deep learning models. It can be used across a range of tasks but has a particular focus on training and inference of deep neural networks.*
- ***Keras :*** *An open-source Python library within Tensorflow that simplifies the process of building and training neural networks. It is a low-level cross-framework language to develop custom components such as layers, models, or metrics that can be used in native workflows in JAX, TensorFlow, or PyTorch — with one codebase.*

6.4 Pre-Trained Model used

- ***VGG-19 :*** *It is a Convolutional Neural Network architecture which is 19 layers deep. It pre-trained on the ImageNet dataset, used for feature extraction.*

- ***EfficientNet*** ***:*** *It is a convolutional neural network architecture and scaling method that uniformly scales all dimensions of depth/width/resolution using a compound coefficient.*

- ***Yolo v8*** ***:*** *It is a pre-trained model from Ultralytics that performs different tasks like object detection, instance segmentation, pose/keypoints detection, oriented object detection and classification.*

6.5 Development Environment used

- ***Kaggle*** ***:*** *It is a data science platform and online community of data scientists and machine learning practitioners. It allows to test the Python code by running it in the container so it can connect to our local testing environment.*

- ***Google Colab*** ***:*** *Colab is a hosted Jupyter Notebook service that requires no setup to use and provides free access to computing resources, including GPUs and TPUs.*

- ***Roboflow*** ***:*** *It is a developer framework for better data collection to preprocessing, and model training techniques. Roboflow accepts various annotation formats.*

Chapter 7

Improved Methods

Improving the performance of a brain tumor detection system involves a combination of advancements in technology, data quality, model architecture, etc. Some methods are :

1. Large and Varied Dataset - Ensure that the dataset used for training the model is large and diverse, covering various types, sizes, and locations of brain tumors.

2. Ensemble methods - Combining multiple models using ensemble techniques like bagging, boosting, or stacking can improve prediction accuracy by leveraging the strengths of different models. Ensemble learning can improve generalization and robustness by reducing the risk of overfitting to specific features in the training data.

3. Domain and task-specific augmentation - Design data augmentation strategies tailored to the characteristics of brain tumor images. This helps the model generalize better to variations in tumor size, shape, and position.

4. Integration of Multiple Imaging Modalities - Integrate information from different imaging modalities (e.g., MRI, CT) to provide a more comprehensive view of the tumor.

5. Use of 3D CNNs : Since MRI images are inherently three-dimensional, using 3D convolutional neural networks (3D CNNs) can capture spatial context across slices, leading to better tumor detection and classification.

6. Transfer Learning with Advanced Pre-trained Models : Using more advanced pre-trained models beyond VGG19, such as ResNet, Inception, or EfficientNet, can significantly improve feature extraction due to their deeper architectures and better performance on a variety of tasks.

7. Advanced Preprocessing : Applying advanced preprocessing techniques such as skull stripping, intensity normalization, and bias field correction specific to MRI data can enhance the quality of the input data.

8. Segmentation Prior to Classification : Using segmentation algorithms to first isolate the tumor region can improve classification by focusing the model on the relevant parts of the image.

9. Hyperparameter Optimization : Employing hyperparameter optimization techniques like grid search, random search, or Bayesian optimization can fine-tune model parameters for optimal performance.

10. Regularization and Dropout : Implementing regularization techniques such as L2 regularization and dropout layers can prevent overfitting and improve model generalization.

By incorporating these improved methods, the brain tumor detection and classification system can achieve higher accuracy, etc. ultimately leading to better diagnostic outcomes.