# 1. INTRODUCTION

Brain tumor diagnosis and treatment provide major problems for the medical field, requiring specialized therapeutic approaches and accurate diagnostic techniques to maximize patient results. Novel approaches to improving the precision and effectiveness of brain tumor identification are presented by recent developments in medical imaging and machine learning technologies. Because of its remarkable capacity to recognize complex patterns and features from radiological pictures, Convolutional Neural Networks (CNNs) have become indispensable instruments in the field of medical image analysis. With the use of large datasets, CNN-based techniques show promise in improving the precision of brain tumor identification.

Gliomas, meningiomas, and pituitary tumors are just a few of the many forms of brain tumors that can occur; each has its own set of problems and treatment options. For example, gliomas are the most prevalent primary brain tumors in adults and are thought to have originated from glial cells. Meningiomas are benign tumors that originate from the meninges, which are the membranes that surround the brain and spinal cord. However, the location of the tumor may affect how severe the symptoms are. Originating from the pituitary gland at the base of the brain, pituitary tumors can cause hormone production disruption and a host of other health problems.

These tumors are dangerous due to their various appearances and clinical histories, in addition to their ability to damage vital brain processes. Headaches, convulsions, altered vision or hearing, cognitive impairments, hormone imbalances, and neurological deficiencies are a few possible symptoms. It is essential to identify these cancers early on in order to plan treatments and intervene promptly. Brain tumors are currently treated with a multimodal strategy that includes targeted medicines, radiation therapy, chemotherapy, and surgery.

The goal of surgery is to remove the tumor as much as possible while maintaining brain function. Chemotherapy and radiation therapy can be used to kill any remaining tumor cells and stop them from coming back.

Furthermore, developments in molecularly targeted drugs and immunotherapy—two types of targeted therapies—offer encouraging paths toward customized treatment regimens. This work suggests a new method for detecting brain tumors using a CNN design based on EfficientNetB1. EfficientNetB1, a computationally efficient and robust feature extraction tool, is the foundation of our model and makes it easier to extract useful features from brain MRI data. Global Average Pooling 2D and dropout regularization are important elements that we incorporated into our model to improve feature extraction and reduce the likelihood of overfitting during training. Furthermore, we incorporate the Gemini Pro Vision model into our framework to expand the scope of our analysis. In order to enhance clinical decision-making processes, the Gemini Pro Vision model enhances our system by offering tailored therapy recommendations based on tumor features and patient-specific parameters. Our project aims to improve brain tumor diagnosis and management by combining state-of-the-art CNN architecture with sophisticated decision-making skills, ultimately leading to better patient treatment and results.

### 1.1 BRAIN TUMOR DETECTION SYSTEM

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 brain is brain tumor. A tumor is nothing but excess cells growing in an uncontrolled manner. Brain tumor cells grow in a way that they eventually take up all the nutrients meant for the healthy cells and tissues, which results in brain failure. Currently, doctors locate the position and the area of brain tumor by looking at the MR Images of the brain of the patient manually. This results in inaccurate detection of the tumor and is considered very time consuming. A Brain Cancer is very critical disease which causes deaths of many individuals. The brain tumor detection and classification system is available so that it can be diagnosed at early stages. Cancer classification is the most challenging tasks in clinical diagnosis. This project deals with such a system, which uses computer, based procedures to detect tumor blocks and classify the type of tumor using Convolution Neural Network Algorithm for MRI images of different patients. Different types of image processing techniques like image segmentation, image enhancement and feature extraction are used for the brain tumor detection in the MRI images of the cancer-affected patients. Detecting Brain tumor using Image Processing techniques its involves the four stages is Image Pre-Processing, Image segmentation, Feature Extraction, and Classification. Image processing and neural network techniques are used for improve the performance of detecting and classifying brain tumor in MRI images.

**MAGNETIC RESONANCE IMAGING (MRI)** Raymond v. Damadian invented the first magnetic image in 1969. In 1977 the first MRI image were invented for human body and the most perfect technique. Because of MRI we are able to visualize the details of internal structure of brain and from that we can observe the different types of tissues of human body. MRI images have a better quality as compared to other medical imaging techniques like X-ray and computer tomography.[8]. MRI is good technique for knowing the brain tumor in human body. There are different images of MRI for mapping tumor induced Change including T1 weighted, T2 weighted and FLAIR (Fluid attenuated inversion recovery) weighted shown in figure.

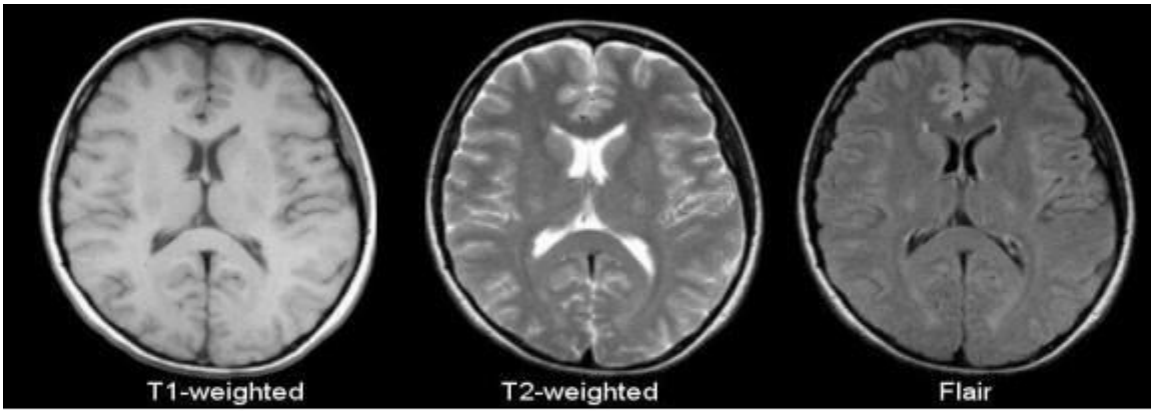


Fig 1.1: MRI Image

The most common MRI sequence is T1 weighted and T2 weighted. In T1 weighted only one tissue type is bright FAT and in T2 weighted two tissue types are Bright FAT and Water both. In T1 weighted the repetition time (TR) is short in T2 weighted the TE and TR is long. The TE an TR are the pulse sequence parameter and stand for repetition time and time to echo and it can be measured in millisecond(ms)[9]. The echo time represented time from the centre of the RF pulse to the centre of the echo and TR is the length of time between the TE repeating series of pulse and echo is shown in figure.

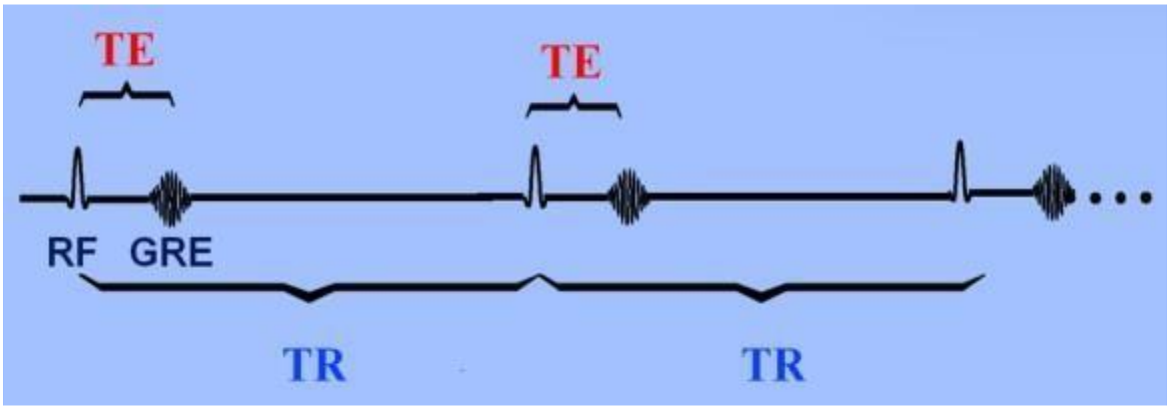


Fig 1.2 Graph

**1.2 APPLICATIONS**

- The main aim of the applications is tumor identification.
- 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. To overcome those problem this application is design.
- It is user friendly application.

## 1.3 OBJECTIVES

- To provide doctors good software to identify tumor and their causes.
- Save patient’s time.
- Provide a solution appropriately at early stages.
- Get timely consultation.

## 1.4 MOTIVATION

The main motivation behind Brain tumor detection 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. This project deals with such a system, which uses computer, based procedures to detect tumor blocks and classify the type of tumor using Convolution Neural Network Algorithm for MRI images of different patients.

## 2. LITERATURE SURVEY

**Paper-1: Image Analysis for MRI Based Brain Tumor Detection and Feature Extraction Using Biologically Inspired BWT and SVM**

- Publication Year: 6 March 2017
- Author: Nilesh Bhaskarrao Bahadure, Arun Kumar Ray, and Har Pal Thethi
- Journal Name: Hindawi International Journal of Biomedical Imaging
- Summary: In this paper using MR images of the brain, we segmented brain tissues into normal tissues such as white matter, gray matter, cerebrospinal fluid (background), and tumor-infected tissues. We used pre-processing to improve the signal-to-noise ratio and to eliminate the effect of unwanted noise. We can used the skull stripping algorithm its based on threshold technique for improve the skull stripping performance.

**Paper-2: A Survey on Brain Tumor Detection Using Image Processing Techniques**

- Publication Year: 2017
- Author: Luxit Kapoor, Sanjeev Thakur
- Journal Name: IEEE 7th International Conference on Cloud Computing, Data Science & Engineering
- Summary: This paper surveys the various techniques that are part of Medical Image Processing and are prominently used in discovering brain tumors from MRI Images. Based on that research this Paper was written listing the various techniques in use. A brief description of each technique is also provided. Also of All the various steps involved in the process of detecting Tumors, Segmentation is the most significant.

**Paper-3: Identification of Brain Tumor using Image Processing Techniques**

- Publication Year: 11 September 2017
- Author: Praveen Gamage
- Journal Name: Research gate
- Summary: This paper survey of Identifying brain tumors through MRI images can be categorized into four different sections; pre-processing, image segmentation, Feature extraction and image classification

**Paper-4: Review of Brain Tumor Detection from MRI Images**

- Publication Year: 2016
- Author: Deepa, Akansha Singh
- Journal Name: IEEE International Conference on Computing for Sustainable Global Development
- Summary: In this paper, some of the recent research work done on the Brain tumor detection and segmentation is reviewed. Different Techniques used by various researchers to detect the brain Tumor from the MRI images are described. By this review we found that automation of brain tumor detection and Segmentation from the MRI images is one of the most active Research areas

**Paper-5: An efficient Brain Tumor Detection from MRI Images using Entropy Measures**

- Publication Year: December 23-25, 2016
- Author: Devendra Somwanshi , Ashutosh Kumar, Pratima Sharma, Deepika Joshi
- Journal Name: IEEE International Conference on Recent Advances and Innovations in Engineering
- Summary: In this paper, we have investigated the different Entropy functions for tumor segmentation and its detection from various MRI images. The different threshold values are obtained depend on the particular definition of the entropy. The threshold values are dependent on the different entropy function which in turn affects the segmented results.

# 3. EXITING WORK & PROPOSED WORKFLOW

## 3.1 OVERVIEW OF EXITING WORK

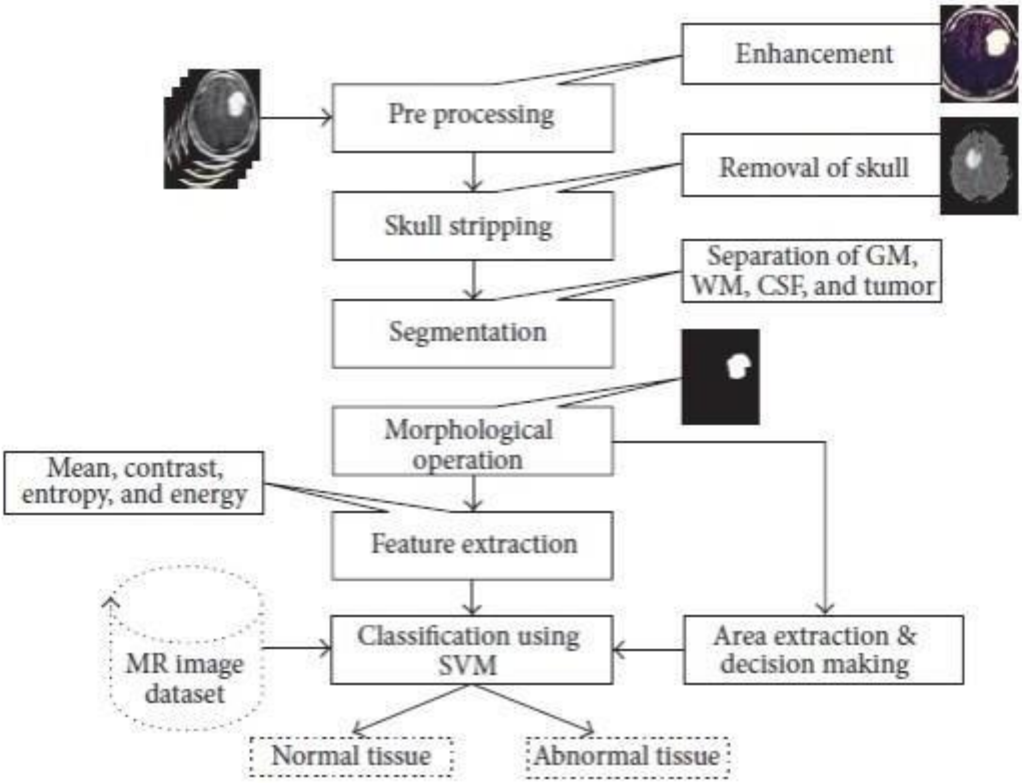


Fig.3.1.Existing work flow of brain tumor detection.

- In the first 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.
- The second stage involves the use of different image processing techniques such as histogram equalization, image segmentation, image enhancement, morphological operations and feature extraction are used for brain tumor detection in the MRI images for the cancer-affected patients.
- This work is introduced one automatic brain tumor detection method to increase the accuracy and decrease the diagnosis time.

- **Image Preprocessing:** As input for this system is MRI, scanned image and it contain noise. Therefore, our first aim is to remove noise from input image. As explained in system flow we are using high pass filter for noise removal and preprocessing.
- **Segmentation:** Region growing is the simple region-based image segmentation technique. It is also classified as a pixel based image segmentation technique since it is involve the selection of initial seed points.

- **Morphological operation:** The morphological operation is used for the extraction of boundary areas of the brain images. This operation is only rearranging the relative order of pixel value, not mathematical value, so it is suitable for only binary images. Dilation and erosion is basic operation of morphology. Dilation is add pixels to the boundary region of the object, while erosion is remove the pixels from the boundary region of the objects.
- **Feature Extraction:** The feature extraction is used for edge detection of the images. It is the process of collecting higher level information of image such as shape, texture, color, and contrast.
- **Connected component labeling:** After recognizing connected components of an image, every set of connected pixels having same gray-level values are assigned the same unique region label.
- **Tumor Identification:** In this phase, we are having dataset previously collected brain MRIs from which we are extracting features. Knowledge base is created for comparison.

## 3.2 PROPOSED WORKFLOW

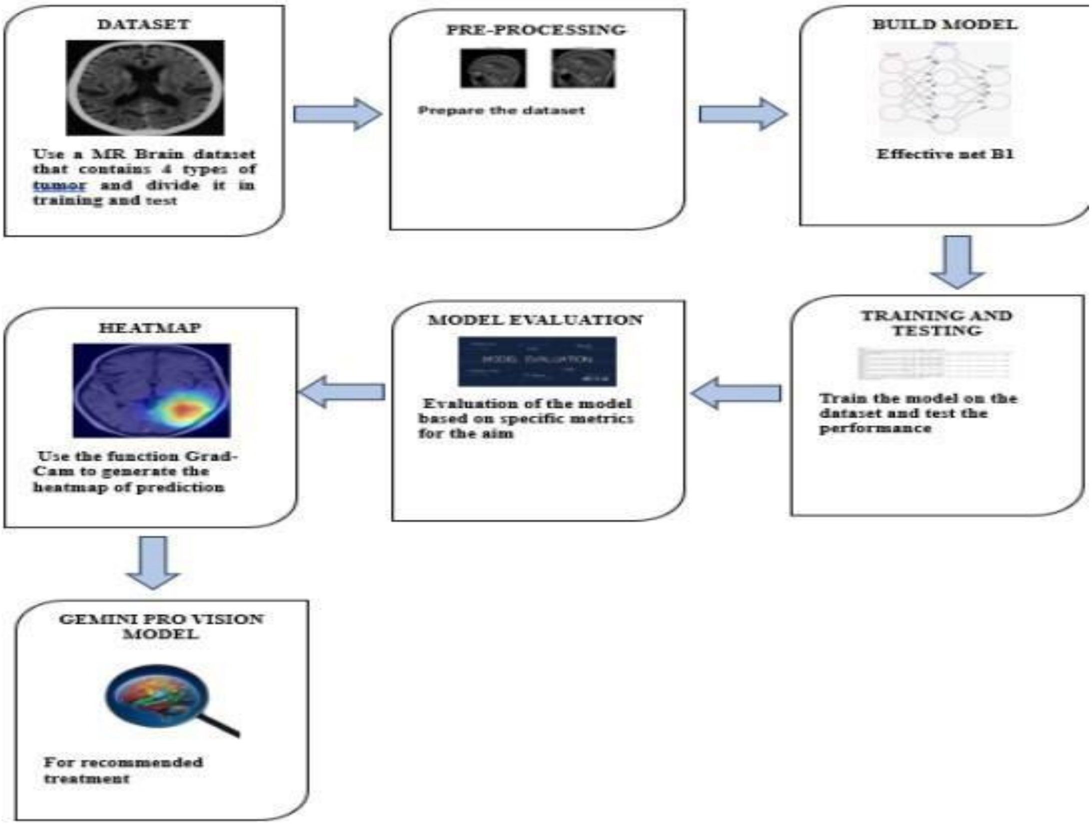


Fig 3.2 Workflow

- **Dataset:** Gliomas, meningiomas, pituitary tumors, and no tumor comprise the four separate groups of MRI scans that make up the dataset used in this study. These categories show several forms of brain tumors in addition to comparison photos of healthy brain tissue. The dataset includes 394 photos for testing and 3,265 images for training. This extensive dataset is essential for brain tumor detection system training and performance assessment.
- **Preprocessing Steps:** To improve the MRI images' quality and usefulness for analysis, a number of preprocessing processes are used before feeding them into the model. The images are first converted to grayscale to facilitate processing, then they are processed using a Gaussian blur filter to reduce noise, binary thresholding is used to segment the images into foreground and background regions, morphological operations such as erosion and dilation are used to refine the image structures, contour detection algorithms are used to detect and delineate tumor boundaries, and finally, the images are cropped based on the contours to focus specifically on the regions of interest containing the brain tumors.

**Model Building**: Based on the EfficientNetB1 model, which is well-known for its efficacy and efficiency in image classification tasks, the brain tumor detection model's fundamental architecture is constructed. Pre-trained weights from the ImageNet dataset training process are used to initialize the model. In order to ensure compatibility with the MRI images frequently utilized in brain tumor identification, the model's input shape is adjusted to (240, 240, 3). In order to combine spatial data and decrease dimensionality, a 2D layer called Global Average Pooling is implemented. To keep overfitting from happening during training, dropout regularization is applied using a 0.5 dropout rate. The final step in multi-class classification involves adding a dense layer with softmax activation, which divides brain tumor images into four classes: glioma, meningioma, pituitary adenoma, and non-tumor.

**Training and Testing data:** Four separate categories—glioma, meningioma, pituitary, and no tumor—are used to organize the training and testing data for the brain tumor identification system. These categories include pictures of normal brain tissue for comparison, as well as representations of various kinds of brain tumors.

**Training Data:** There are 3,265 MRI pictures in the training dataset. The method for detecting brain tumors is trained using these photos. In order to correctly classify new images, the system must first learn to identify patterns and features in the MRI images that differentiate between the various categories.

**Testing Data:** There are 394 MRI pictures in the testing dataset. These pictures are used to evaluate the effectiveness of the brain tumor detection system; they are not part of the training set. These hidden pictures are sent into the system, and its accuracy in categorizing them into the relevant groups (glioma, meningioma, pituitary, or no tumor) is evaluated. In order to assess the trained model's performance in real-world events and gauge how effectively it generalizes to new, unknown data, testing data is necessary. This extensive dataset is essential for the brain tumor detection system's training and performance assessment. It enables investigators and designers to evaluate the system's overall performance, sensitivity, specificity, and accuracy prior to clinical or diagnostic implementation.

**Module Evaluation**: The evaluation findings on the testing dataset showed that the model performed exceptionally well, with an astounding accuracy rate of 98%. The model's great precision in classifying different kinds of brain tumors across all categories is further demonstrated by the confusion matrix analysis. In particular, the model demonstrated its resilience in practical situations by achieving impressive accuracy in differentiating between pituitary tumors, gliomas, meningiomas, and normal brain tissue. Furthermore, the low loss value of 0.071 and computed testing accuracy of 98.22% highlight the model's dependability and efficacy in producing precise predictions on unseen MRI data. In general, the assessment metrics confirm the model's effectiveness and demonstrate its possible application in clinical contexts for the identification and diagnosis of brain tumors.

**Grad-CAM Implementation**: Gradient-weighted Class Activation Mapping (Grad-CAM) is used to obtain information about the areas of the MRI images that contribute to the model's predictions. By examining the gradients entering the CNN's last convolutional layer, this method creates heatmaps. The regions of interest are highlighted in these heatmaps, which facilitates the qualitative evaluation of the model's decision-making process.

**Gemini Pro Vision:** The research incorporates the Gemini Pro Vision model, which uses sophisticated decision-making algorithms to assess tumor features including type and location in addition to patient-specific variables, in addition to tumor identification. Clinical decision-making and patient care are improved by this integration, which makes it possible to create individualized therapy recommendations for each patient. Following an explanation of the methodology used in this investigation to identify and analyze brain tumors, we now focus on the outcomes of the trials that were carried out. The model evaluation results, heatmap analysis,

### 3.2.1 WORKING OF CNN MODEL

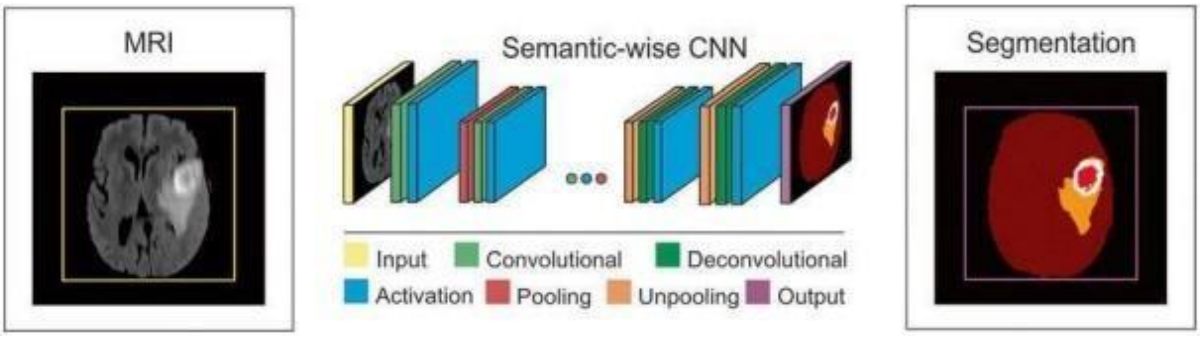


Fig.3.3.Working of CNN model for brain tumor detection

- **Layer of CNN model**: o Convolution 2D o MAX Poolig2D o Dropout o Flatten o Dense o Activation
- **Convolution 2D:** In the Convolution 2D extract the featured from input image. It given the output in matrix form.
- **MAX Poolig2D:** In the MAX polling 2D it take the largest element from rectified feature map.
- **Dropout**: Dropout is randomly selected neurons are ignored during training.
- **Flatten**: Flatten feed output into fully connected layer. It gives data in list form.
- **Dense**: A Linear operation in which every input is connected to every output by weight. It followed by nonlinear activation function.
- **Activation:** It used Sigmoid function and predict the probability 0 and 1.
- In the compile model we used binary cross entropy because we have two layers 0 and 1.
- We used Adam optimizer in compile model.
- **Adam:-**Adaptive moment estimation. It used for non convex optimization problem like straight forward to implement.
  - Computationally efficient.
  - Little memory requirement.

### 3.2.2 EfficientNet B1

For the implementation of brain tumor detection in our final year project, we utilized EfficientNetB1, a convolutional neural network architecture known for its efficient scaling of width, depth, and resolution. Initially, our dataset underwent preprocessing, where images were resized to dimensions suitable for EfficientNetB1 input (typically 240x240) and pixel values were normalized to the range [0, 3]. Leveraging pre-trained weights from ImageNet, we instantiated the EfficientNetB1 model using TensorFlow, incorporating transfer learning techniques. This involved fine-tuning the model on our brain tumor dataset, freezing layers up to a certain depth, and adding custom layers tailored for brain tumor detection. Throughout the training process, we employed data augmentation to diversify the training data and mitigate overfitting, monitoring progress using standard metrics such as loss and accuracy. Evaluation of the trained model on a separate validation dataset was performed, assessing performance using metrics including accuracy, precision, recall, and F1-score. Hyperparameter tuning, including adjustments to learning rate and batch size, was conducted to optimize model performance. Upon achieving satisfactory results, the model was deployed for real-world applications.

### 3.2.3 GEMINI PROVISION MODEL

In addition to brain tumor detection, our project integrates the Gemini Pro Vision model to provide detailed findings and recommend treatments based on the detected tumors. Gemini Pro Vision, a state-of-the-art medical imaging analysis system, employs advanced deep learning algorithms to analyze MRI scans and provide comprehensive insights into various neurological conditions. By integrating Gemini Pro Vision into our system, we enhance the diagnostic capabilities of our application, enabling users to receive detailed reports on tumor characteristics, such as size, location, and morphology. Furthermore, leveraging the model's extensive knowledge base and medical expertise, our system recommends personalized treatment options tailored to each patient's specific condition. This integration not only enhances the clinical utility of our application but also empowers healthcare professionals with valuable insights and recommendations for patient care. The seamless integration of Gemini Pro Vision underscores our commitment to leveraging cutting-edge technology to improve the diagnosis and treatment of brain tumors, ultimately enhancing patient outcomes and healthcare delivery.

# 4. SOFTWARE AND HARDWARE SPECIFICATION

## 4.1 HARDWARE REQUIREMENTS

- Hard Disk : 500GB and Above
- RAM : 4GB and Above
- Processor : I3 and Above

## 4.2 SOFTWARE REQUIREMENTS

- Operating System : Windows 7, 8, 10 (64 bit)
- Software : Python, Docker
- Tools :Google collab, VS Code

## 4.3 SOFTWARE DESCRIPTION:

➢ **PYTHON**

• Python is a free, open-source programming language. Therefore, all you have to do is install Python once, and you can start working with it. Not to mention that you can contribute your own code to the community. Python is also a cross-platform compatible language. So, what does this mean? Well, you can install and run Python on several operating systems.

• Python is also a great visualization tool. It provides libraries such as Matplotlib, seaborn and bokeh to create stunning visualizations.

➢ **B. PANDAS**

- Pandas is a popular Python package for data science, and with good reason: it offers powerful, expressive and flexible data structures that make data manipulation and analysis easy, among many other things. The Data Frame is one of these structures. Pandas is a highlevel data manipulation tool developed by Wes McKinney. It is built on the Numpy package and its key data structure is called the Data Frame. Data Frames allow you to store and manipulate tabular data in rows of observations and columns of variables.
- Pandas is built on top of the NumPy package, meaning a lot of the structure of NumPy is used or replicated in Pandas. Data in pandas is often used to feed statistical analysis in SciPy, plotting functions from Matplotlib, and machine learning algorithms in Scikit-learn. There are two types of data structures in pandas: Series and Data Frames.

a) Series: A pandas Series is a one-dimensional data structure

b) Data Frame: A pandas Data Frame is a two (or more) dimensional data structure basically a table with rows and columns.

- **GOOGLE COLLAB:**

  Google Colab, or Colaboratory, serves as a cloud-based platform offered by Google, facilitating Python code execution within a browser environment. Its accessibility from any device with an internet connection and web browser streamlines project work. Integration with Google Drive enables easy saving and sharing of project files. A notable feature is the provision of free GPU and TPU resources, significantly accelerating machine learning computations, particularly beneficial for tasks like training deep learning models. Operating within a Jupyter Notebook environment, users can organize code into cells for iterative development and documentation. With pre-installed libraries such as TensorFlow and PyTorch, it's well-suited for machine learning tasks. Collaboration features allow real-time multiple-user engagement, making it ideal for team projects. Additionally, resource management tools enable users to monitor and select between CPU, GPU, or TPU resources based on project needs. These aspects collectively make Google Colab an invaluable asset for projects like brain tumor detection, offering convenience, efficiency, and powerful computational resources.

- **BACKEND:**

  For the backend implementation of our brain tumor detection system, we opted for Flask, a lightweight web framework for Python, coupled with Docker for containerization. Flask facilitated the development of our RESTful API endpoints, enabling seamless communication between the front end and machine learning model. Leveraging Flask's simplicity and flexibility, we designed endpoints to handle image uploads, model predictions, and result retrieval, providing a user-friendly interface for interacting with our system. Docker was instrumental in containerizing our Flask application, ensuring consistency and portability across different environments. By encapsulating our application and its dependencies within Docker containers, we achieved easy deployment and scalability, streamlining the integration process with other components of our system. Overall, the combination of Flask and Docker served as a robust backend infrastructure for our brain tumor detection system, offering reliability, efficiency, and flexibility for both development and deployment phases.

# 5. IMPLEMENTION

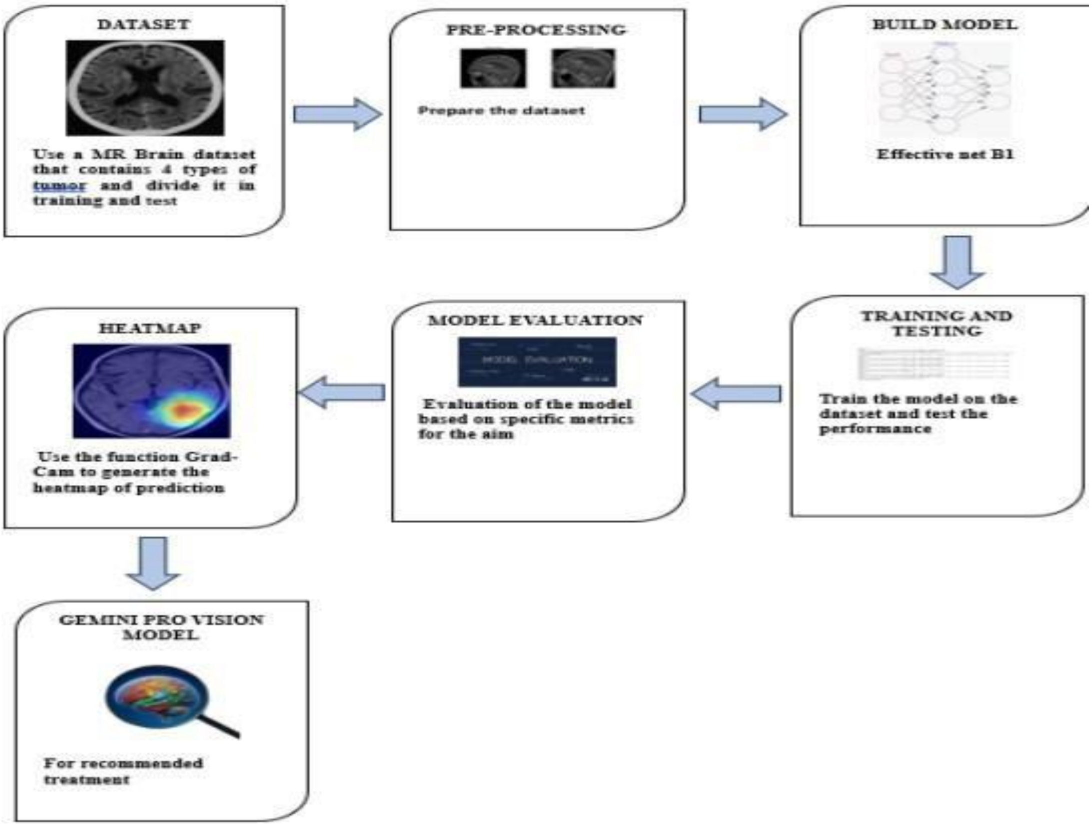


Fig.5.1 Proposed Methodology

- **Dataset:** Gliomas, meningiomas, pituitary tumors, and no tumor comprise the four separate groups of MRI scans that make up the dataset used in this study. These categories show several forms of brain tumors in addition to comparison photos of healthy brain tissue. The dataset includes 394 photos for testing and 3,265 images for training. This extensive dataset is essential for brain tumor detection system training and performance assessment.
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# TESTING

Performance Evaluation: Training Accuracy: With the help of the EfficientNetB1 architecture, the CNN model that was constructed was able to obtain an astounding 99% accuracy on the training set. This shows how well the model learned from the training dataset and was able to generalize, identifying the underlying patterns and characteristics linked to the classification of brain tumors.

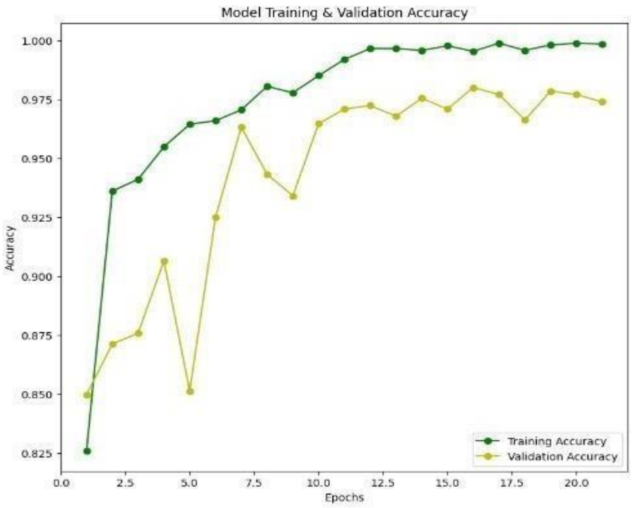


Fig.6 Training Accuracy

**6.1 Testing Accuracy**: The model demonstrated remarkable accuracy of 98% after being evaluated on the testing dataset. This strong performance on unknown data demonstrates the model's capacity for efficient generalization and precise prediction on novel, unknown MRI scans.

confusion matrix: Based on a testing dataset of 394 MRI pictures, the confusion matrix shows the model's performance in terms of categorization. Out of 100 photos, the model correctly identified 95 glioma tumors; only 4 misclassified as meningiomas and 1 as pituitary tumors. In addition, all 104 tumors of meningioma, 105 tumors of the pituitary, and 74 samples that were not malignancies were accurately classified. This illustrates how well the model can reliably identify between various forms of brain tumors. The model's testing accuracy was determined to be 98.22%, with a loss of 0.071. These metrics show that the model's predictions on hypothetical MRI images have a high degree of accuracy and a low error rate.

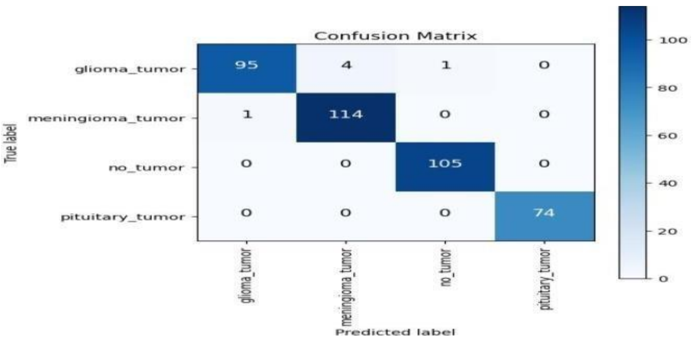


**fig 6.2 Predicted Label**

**6.2 Classification report**: Glioma, meningioma, pituitary adenoma, and non-tumor are the four classes for which themodel's performance is evaluated in detail in the classification report. The model shows robustness and efficacyin classifying brain tumor kinds, with good precision, recall, and F1-score metrics across all classes. On the testing dataset, the model specifically achieves an overall accuracy of 98%,

demonstrating its capacity to correctly categorize MRI pictures into their appropriate categories.

| | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| 0 | 0.99 | 0.95 | 0.97 | 100 |
| 1 | 0.97 | 0.99 | 0.98 | 115 |
| 2 | 0.99 | 1.00 | 1.00 | 105 |
| 3 | 1.00 | 1.00 | 1.00 | 74 |

Fig 6.2.1 Classification Report

**6.3 Visualization:** Moreover, the Grad-CAM heatmaps' visual representation offered information on the MRI image regions that were most important to the model's predictions. By emphasizing the areas of great importance, these heatmaps improved interpretability and facilitated the qualitative evaluation of the model's decision-making process.

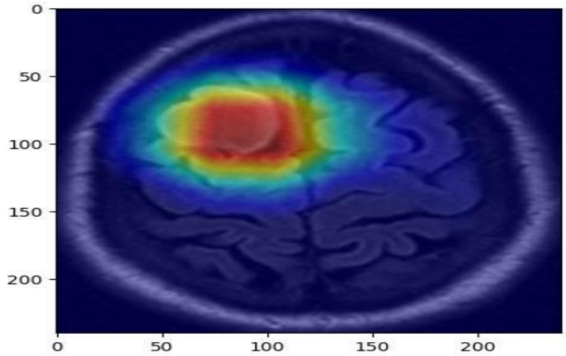


Fig 6.3 Heatmap

**6.4 Gemini pro vision model results:** By utilizing tumor features and patient-specific parameters, the Gemini Pro Vision model was integrated to enable the creation of customized therapy recommendations for individual patients. By providing practical insights for treatment planning and decision-making, this integration improves the developed system's clinical value.


Fig 6.4 Gemini Results

# SNAPSHOTS

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## Brain Tumor Detection

The human brain is probably one of the most complex single objects on the face of the earth; I think it is, quite honestly.

Choose File img 1.jpg

Image selected successfully.

Submit

Tumor Type: glioma_tumor

Check with AI

The MRI image shows a large, round mass in the left frontal lobe of the brain. The mass is isointense to gray matter on T1-weighted images and hyperintense on T2-weighted images. There is surrounding edema. The mass is most likely a glioma, which is a type of primary brain tumor. The recommended treatment for a glioma is surgery to remove the tumor. If the tumor is inoperable, radiation therapy and chemotherapy may be used.

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# Brain Tumor Detection

The human brain is probably one of the most complex single objects on the face of the earth; I think it is, quite honestly.

Choose File img 3.jpg

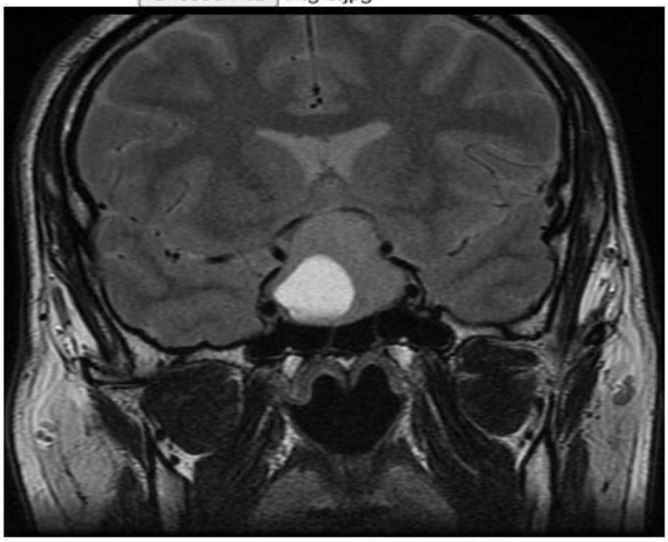

Image selected successfully.

Submit

Tumor Type: pituitary_tumor

Check with AI

**Findings:** The MRI image shows a 1.5 cm enhancing mass in the sellar region with suprasellar extension. The mass is isointense on T1-weighted images and hyperintense on T2-weighted images. There is no evidence of invasion into the surrounding structures. **Differential Diagnosis:** - Pituitary adenoma - Craniopharyngioma - Rathke's cleft cyst - Glioma - Meningioma **Recommended Treatment:** Given the location and appearance of the mass, the most likely diagnosis is a pituitary adenoma. The recommended treatment for a pituitary adenoma is surgery to remove the mass. If surgery is not possible, radiation therapy may be an option.

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Choose File img 3.jpg

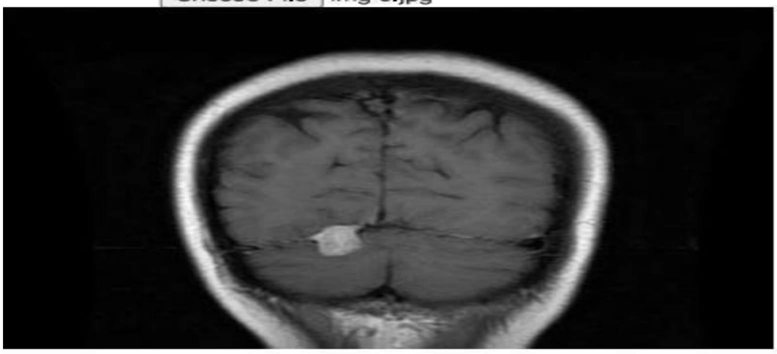

Image selected successfully.

Submit

Tumor Type: meningioma_tumor

Check with AI

**Findings:** There is a 2.8 x 2.4 x 2.2 cm enhancing mass lesion in the region of the right cerebellopontine angle cistern. The mass appears to be isointense on T1, and hypointense on FLAIR. There is surrounding vasogenic edema. There is no evidence of hydrocephalus. **Differential Diagnosis:** -Vestibular schwannoma -Meningioma -Glioma **Recommended Treatment:** Given the location and appearance of the mass, the most likely diagnosis is a vestibular schwannoma. Treatment options include observation, surgery, and radiation therapy. The best treatment option for this patient will depend on their individual circumstances and preferences.

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Choose File img 2.jpg

Image selected successfully.

Submit

Tumor Type: glioma_tumor

Check with AI

**Findings:** There is a large, enhancing mass lesion in the right frontal lobe. The mass is causing significant mass effect, with compression of the right lateral ventricle and surrounding brain tissue. There is also a smaller enhancing lesion in the left frontal lobe. **Differential Diagnosis:** - GBM - Anaplastic astrocytoma - Metastasis **Recommended Treatment:** - The patient should undergo a biopsy of the mass lesions to confirm the diagnosis. - If the diagnosis is confirmed, the patient should be treated with surgery, radiation therapy, and chemotherapy.

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# CONCLUSION

Using EfficientNetB1 as the foundation model, we created a convolutional neural network (CNN) architecture in this study to establish a brain tumor detection system. GlobalAveragePooling2D, Dropout for regularization, and a Dense layer with softmax activation for classification comprised our unique CNN design. Using MRI scans, we trained our algorithm to identify several forms of brain cancers with high accuracy. It worked well, correctly classifying four different kinds of brain tumors with a high degree of accuracy. We also included the Gemini Pro Vision model, which is another useful tool. Based on its analysis, this tool may provide the most effective course of treatment for the specific type of tumor.

# REFERENCES

[1] N. Sravanthi, Nagari Swetha Poreddy, Rupa Devi Siliveru, Rachana, Suwarna, Gothane, N. Sateesh, Brain Tumor Detection Using Image Processing,2021.

[2] P. Sankar Ganesh, T. Selva Kumar, Mukhesh Kumar, S. Rajesh Kumar, Brain Tumor Detection and Classification Using Image Processing Techniques,2021.

[3] Ouiza Nait Belaid and Malik Loudini, Classification of Brain Tumor by Combination of Pre-Trained VGG16 CNN, 2020.Chengwei Liu, Yixiang Chan, Syed Hasnain Alam Kazmi, Hao Fu, “Financial Fraud Detection Model: Based on Random Forest,” International Journal of Economics and Finance, Vol. 7, Issue. 7, pp. 178-188, 2015.

[4] Dinesh M. Barode1, Rupali S. Awhad2, Seema S. Kawathekar3, Brain Tumor Detection using Digital Image Processing,2023.

[5] Mugdha Singh1, Vineet Singh2, Shikha Singh3, Pooja Khanna4, Evaluation of Data Sets and Algorithms for Brain Tumor Detection Using MRI Images: A Python-Based Approach, 2023 [6] N. Sravanthi, Nagari Swetha Poreddy, Rupa Devi Siliveru, Rachana, Suwarna, Gothane,N. Sateesh,Brain Tumor Detection Using Image Processing,2021

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