

# A Machine Learning Approach for Brain Tumor Detection Using CNN Algorithm

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## ABSTRACT

Designing automated systems for extracting and identifying brain tumors, including their specific types, from Magnetic Resonance Images (MRIs) is one of the most researched areas of this era. Brain tumors are a crucial cause of human death every year, with around 50% of diagnosed patients succumbing to primary brain tumors worldwide annually. Healthcare professionals use electronic modalities to diagnose brain tumors, and Magnetic Resonance Imaging is one of the most widely used and popular modalities for brain tumor diagnosis. While 2D MRI provides a restricted view of the brain, 3D MRI offers a comprehensive perspective. This work aims to create an automatic system for swift brain tumor diagnosis, especially in critical situations. This system utilizes MRI tests and image processing techniques such as segmentation to identify the type of tumor. The image captured after the slide test undergoes processing to detect the occurrence and specific types of brain tumors. Subsequently, the classification algorithm, including Machine Learning algorithms, determines the tumor analysis. Finally, all the relevant information will be stored in a database. The system demonstrates high accuracy in tumor segmentation and type identification, as evidenced by the results.

**Keywords :** Brain tumor, 3D MRI image, Segmentation, Machine Learning algorithm, CNN (Convolutional Neural Networks), Pooling.

## I. INTRODUCTION

### a) Brain Tumor

A brain tumor is an irregular and uncontrolled proliferation of cells within the brain or the central spinal canal. These growths can be categorized into two

primary types: benign tumors, which are non-cancerous and typically exhibit slow growth, and malignant tumors, comprised of cancerous cells that may expand more rapidly, potentially invading surrounding tissues. Brain tumors may originate either within the brain itself (primary tumors) or result from

the dissemination of cancer cells from other parts of the body (metastatic or secondary tumors). The presence of a brain tumor has the potential to disrupt normal brain functions by exerting pressure on adjacent structures, leading to various neurological symptoms such as headaches, seizures, and cognitive impairments. Diagnosis often involves the use of medical imaging techniques such as MRI or CT scans, and treatment options may encompass surgery, radiation therapy, chemotherapy, or a combination of these modalities, contingent upon the type and stage of the tumor. Timely detection and intervention play a pivotal role in effectively managing and improving outcomes for individuals affected by brain tumors.

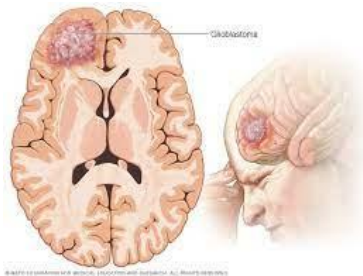


Fig-1 – Brain tumor

## b) Brain Components

- **Cerebrum** -- is the major part of the brain. Which contains two cerebral hemispheres on both sides of the brain in such a way that each of them control the opposed side of the body. It is divided into 4 lobes:
  - The frontal lobe is responsible for feelings, action, sensitive speech, and solving problems.
  - The parietal lobe is responsible for sensations, like pain, temperature and pressure.
  - The temporal lobe is responsible for special senses like vision and hearing, memory, and words recognition.
  - The occipital lobe is responsible for vision control.

- **Cerebellum**-- is a portion of the brain which is below to the cerebrum, and coordinates balance, functioning of the identical side.
- **The brain stem connects** cerebellum and spinal cord and it passes messages to do functioning of human body parts is organized by the cerebrum and cerebellum by passing via brain Stem
- **Meninges**-- membranes environs and shields the stem and brain. Cerebrospinal fluid is prepared close to the epicenter of the brain, in lateral ventricles. CSF flows around the spinal cord and brain between arachnoid.

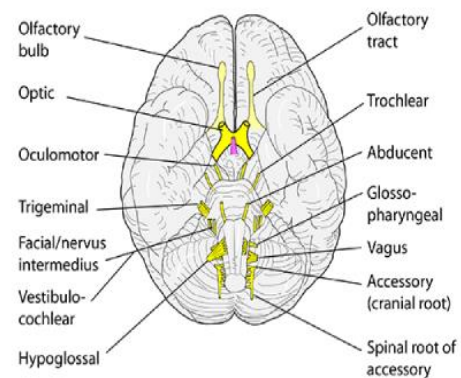


Fig-2:Brain Components

## c) Types of Brain Tumour

- **Glioma**  
Glioma is a type of brain tumor that originates in the glial cells of the brain. Glial cells are supportive cells that surround and provide nourishment to neurons. There are different types of glial cells, and gliomas are named based on the specific type of glial cell they affect
- **Meningiomas**  
Meningiomas are a type of primary brain tumor that originates from the meninges, which are the three layers of protective tissues surrounding the brain and spinal cord. The meninges include the dura mater, arachnoid mater, and pia mater. Meningiomas account for approximately 30% of all primary brain tumors.
- **Pituitary**  
A pituitary tumor, also known as a pituitary adenoma, is a type of primary brain tumor that originates in the

pituitary gland, a small, pea-sized gland located at the base of the brain. Despite being considered a brain tumor, the pituitary gland is outside the brain's protective barrier, known as the blood-brain barrier.

## II. RELATED WORKS

Detecting and analyzing the brain tumor at the earlier stage is an essential one which reduces the possibility to be a victim. Many examinations were conducted by various researchers and finally achieved in identifying several models to detect the presence of brain tumor using machine learning techniques. Here, let us see a brief review of some of the researches which contribute to the detection of brain tumor.

Mohammad Shahjahan Majib, T. M. Shahriar Sazzad, and Md. Mahbubur[1] Rahman present a comprehensive framework for detecting brain tumor cells using MRI images. They emphasize the critical importance of accurate diagnosis in effective treatment. The proposed framework addresses challenges in existing approaches by incorporating morphological operations to enhance tumor cell identification while eliminating undesirable segmentation. The study covers brain tumor classification, the significance of precise analysis using MRI, and a proposed framework involving image acquisition, pre-processing, segmentation, feature extraction, region identification, and classification. Experimental results demonstrate an impressive average accuracy rate of 96.23% across three image batches, showcasing the superior performance of their framework compared to existing methods.

In a distinct approach, Bindhan Biswas, Hossaiian Shahid Soroardi, and Mohammed J. Islam[2] focus on brain tumor detection with tumor region analysis using adaptive thresholding and morphological operations. Their method adapts to diverse intensity values in MRI FLAIR images, ensuring efficient and accurate tumor detection. The proposed technique

achieves commendable accuracy rates of 95% and 89.78% on BRATS 2013 and 2015 datasets, respectively. The study involves 3D to 2D image conversion, set theory for tumor extraction, and the application of adaptive thresholding and morphological operations. Comparative analysis with existing methods and a detailed confusion matrix for BRATS 2013 dataset validate the efficacy of their proposed technique.

Ms. Aisha Zahid Junejo, Dr. Sheeraz A. Memon, and Ms. Isha Zameer Memon[3] focus on precise brain tumor segmentation within 3D MRI images using the watershed algorithm. The study employs preprocessing techniques, including image enhancement and computation of gradient magnitudes, to improve clarity and feature distinction. Accuracy assessment is conducted using DICE Similarity Coefficient and Intersection Over Union metrics, providing quantitative measures for segmentation effectiveness. The research contributes to the field by providing a comprehensive comparison of various tumor segmentation techniques, shedding light on their strengths and limitations.

The study by Avigyan Sinha, Aneesh R P, Malavika Suresh, Nitha Mohan R, Abinaya D, and Ashwin G Singerji [4] takes a deep learning approach to enhance brain tumor detection and classification. Leveraging image processing and deep learning, their research focuses on detecting and classifying malignant brain tumors from MRI images. The proposed system adopts a multi-step approach, incorporating segmentation before and after classification. The study employs Convolutional Neural Networks (CNN), Keras, and TensorFlow for MRI brain image classification, demonstrating the efficiency of deep learning for improved tumor detection.

In a different perspective, T.D.L. Gayanga, G.P.S.N Pathirana, and T.C. Sandanayake [5] focus on the detection and classification of cancerous brain tumors through the analysis of MRI images. Their research

utilizes a substantial dataset of 3604 images, encompassing three distinct types of brain tumors. Pre-processing techniques such as median filtering and contrast-limited adaptive histogram equalization enhance image quality. The study introduces a multi-step methodology involving skull stripping and the watershed algorithm for precise delineation of tumor boundaries. Notably, they propose a novel approach for automatic and reliable edge detection based on Convolutional Neural Networks (CNN), contributing valuable insights into innovative techniques for improved medical imaging analysis.

## Algorithm

### A) What is CNN?

Convolutional Neural Networks (CNNs) are a class of deep learning models designed for processing structured grid data, such as images. Comprising convolutional layers that apply filters to input data, these networks excel in automatically learning hierarchical representations of features, progressively capturing more complex patterns. CNNs' architecture typically includes convolutional, pooling, and fully connected layers, enabling effective feature extraction, spatial down sampling, and global context learning, respectively. Widely used in computer vision tasks, CNNs have proven instrumental in image classification, object detection, and segmentation, demonstrating their versatility and robust performance across various visual recognition tasks.

### B) Convolutional Neural Networks Architecture

Our proposed Convolutional Neural Network (CNN) architecture is designed to effectively capture spatial hierarchies and learn discriminative features from input images. The architecture consists of several key components:

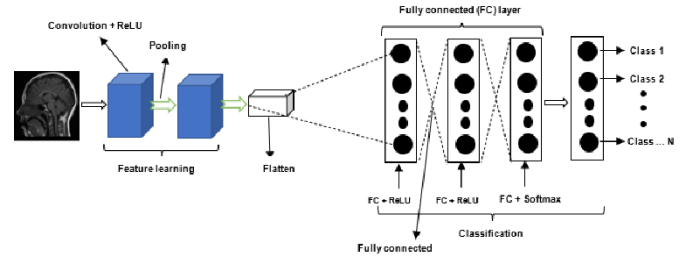


Fig-3: CNN Architecture

B)

#### i) Convoluting Layers:

Convolutional layers are a fundamental component of Convolutional Neural Networks (CNNs) designed to capture hierarchical features from input data. The convolution operation involves applying filters (also known as kernels) to the input data, resulting in feature maps. Each filter detects specific patterns in the input, helping the network recognize increasingly complex features. The size and number of filters are hyperparameters that influence the capacity of the network to learn representations. The convolutional layers are typically followed by activation functions, such as Rectified Linear Units (ReLU), introducing non-linearity.

#### ii) Pooling Layer:

Pooling layers follow each convolutional layer to down sample the spatial dimensions of the feature maps, reducing computational complexity and focusing on the most salient information. We employ max-pooling layers, which retain the maximum activation in each local region.

#### Maximum Pooling Layer:

The Max Pooling layer in our Convolutional Neural Network (CNN) for brain tumor classification serves a pivotal role in down sampling the spatial dimensions of feature maps while retaining crucial information. Implemented after convolutional layers, this layer involves subdividing each feature map into non-overlapping regions and selecting the maximum value from each region. This down sampling mechanism not only reduces computational complexity but also

enhances the network's ability to focus on the most salient features, facilitating robust feature extraction. The Max Pooling layer aids in capturing invariant representations, contributing to the overall effectiveness of our CNN model in discerning pertinent patterns indicative of brain tumor characteristics.

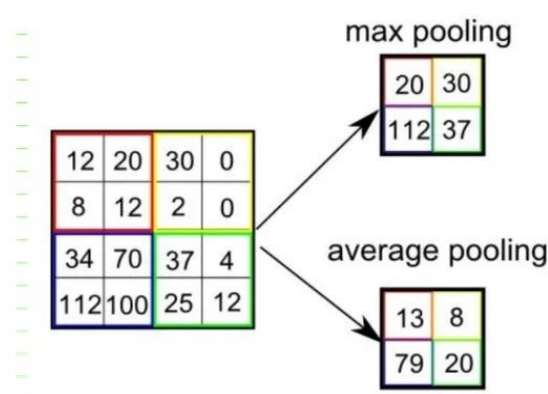


Fig-4: Maximum Pooling Layer

### iii) Fully Connected Layer:

The Fully Connected layer in our Convolutional Neural Network (CNN) for brain tumor classification functions as the final stage of the network, providing a global understanding of the learned features. Following the convolutional and pooling layers, the Fully Connected layer connects all neurons, allowing the model to comprehend complex relationships in the feature space. This layer consolidates the spatial hierarchies captured by preceding layers and produces an output that facilitates tumor classification. The activation function applied after the Fully Connected layer introduces non-linearity, enhancing the network's capacity to discern intricate patterns associated with brain tumor characteristics.

### iv) Activation Function:

#### 1) RLU(Rectified Linear Units):

The Rectified Linear Unit (ReLU) activation function is crucial in Convolutional Neural Networks (CNNs) for brain tumor classification. It introduces non-linearity by allowing the positive values to pass through unchanged, facilitating the modeling of

complex relationships within the data. Applied after convolutional and fully connected layers, ReLU ensures that only positive features are activated, enhancing the network's capacity to capture and represent relevant information associated with brain tumor characteristics. This non-linear transformation plays a key role in the effective learning and discrimination capabilities of the CNN, contributing to its overall performance in brain tumor classification tasks.

#### 2) Sigmoid Function:

The Sigmoid activation function is utilized in the Convolutional Neural Network (CNN) for brain tumor classification to introduce non-linearity and enable the modeling of complex relationships within the data. Applied to the network's output, the Sigmoid function squashes the output values between 0 and 1, effectively transforming the continuous input into a probability-like score. This is particularly valuable in binary classification tasks, as it facilitates the interpretation of the network's prediction as the likelihood of a brain tumor presence. The Sigmoid activation function is instrumental in ensuring the CNN outputs meaningful and interpretable results for accurate tumor classification.

#### v) Dense Layer:

The Dense layer in our CNN for brain tumor classification is a critical component responsible for capturing global patterns and relationships in the learned features. Following the convolutional and pooling layers, the Dense layer connects all neurons, allowing the network to comprehend intricate spatial hierarchies. It consolidates information from the previous layers and produces an output that facilitates tumor classification. With an activation function applied after the Dense layer, such as Rectified Linear Unit (ReLU), non-linearity is introduced, enhancing the network's capacity to discern complex patterns associated with brain tumor characteristics.



### C) RGB Conversion:

In the context of image processing for computer vision applications, the RGB (Red, Green, Blue) color model serves as a fundamental representation of color information in digital images. Each pixel in an RGB image is characterized by three channels corresponding to the intensity of red, green, and blue light, respectively. The values in these channels range from 0 to 255, indicating the intensity of each color component. The conversion to RGB, as employed in this study by using the “.convert("RGB")” method on the image data, is crucial for ensuring a consistent representation of color information across various image modalities. This process standardizes the image format, enabling uniform treatment of color data and facilitating subsequent image processing tasks. The RGB conversion is particularly relevant in scenarios where the original image may be in a different color mode, such as grayscale, ensuring compatibility with algorithms and analyses that rely on the three-channel RGB format. This standardized representation lays the foundation for accurate and comprehensive investigations into computer vision methodologies and applications.

## III. METHODOLOGY

### i. Data Collection and Preprocessing:

First, gather a diverse dataset of sign language gestures, ensuring that it includes various signs, lighting conditions, and backgrounds. Then, preprocess the images by resizing them to a consistent input size, normalizing pixel values, and augmenting the data to improve model generalization.

### ii. Data Splitting:

Split the dataset into training and validation sets, using a common split ratio of 80% for training and 20% for validation.

### iii. Model Selection:

Choose a suitable architecture for your CNN. Mobile Net is a good choice for its efficiency on mobile devices. You can use pre-trained models or train from scratch.

### iv. Transfer Learning:

Utilize transfer learning by leveraging a pre-trained Mobile Net model on a large dataset (like ImageNet) and then fine-tune the model on your sign language dataset to adapt it to your specific task.

### v. Model Architecture

Modify the last few layers of the Mobile Net architecture to match the number of classes in your sign language dataset. Add a global average pooling layer and a dense output layer.

### vi. Training:

Train the model on the training set while monitoring performance on the validation set. Use techniques such as early stopping to prevent overfitting.

### vii. Evaluation:

Evaluate the trained model on the testing set to assess its generalization performance, utilizing metrics such as accuracy.

### Web Setup

In the upper-right corner of any page, select, then click New Repository. Type a short, memorable name for your repository. Optionally, add a description of your repository. ... Choose a repository visibility. ... Select Initialize this repository with a README. Click Create repository

After the process is done, open the streamlined website Log into the account, And link with the GitHub account. Thus, our website is ready for use. We can edit the website by changing the code on GitHub

GitHub Docs Repositories/Work with Files/Managing Files Edit Files Editing files You can edit files directly on GitHub in any of your repositories using the file editor. In this article, editing files in your repository Editing files in another user's repository Editing files in your repository Tip: If a repository has any protected branches, you can't edit or upload files in the protected branch using GitHub. For more information, see

"About protected branches." You can use GitHub Desktop to move your changes to a new branch and commit them. For more information, see "Committing and reviewing changes to your project in GitHub Desktop." Note: GitHub's file editor uses Code Mirror in Code Mirror in your repository; browse to the file you want to edit. In the upper-right corner of the file view, click to open the file editor. Screenshot of a file. In the header, a button labeled with a pencil icon is outlined in dark orange. Note: Instead of editing and committing the file using the default file editor, you can optionally choose to use the github dev code editor by selecting the drop-down menu and clicking github.dev. You can also clone the repository and edit the file locally via GitHub Desktop by clicking GitHub Desktop. Screenshot of a file. In the header, a downward-facing triangle icon is outlined in dark orange. In the text box, make any changes you need to the file. Above the new content, click Preview. Screenshot of a file in edit mode. Above the file's contents, a tab labeled "Preview" is outlined in dark orange. Click Commit Changes... In the "Commit message" field, type a short, meaningful commit message that describes the change you made to the file. You can attribute the commit to more than one author in the commit message. For more information, see "Creating a commit with multiple authors." If you have more than one email address associated with your account on GitHub.com, click the email address drop-down menu and select the email address to use as the Git author email address. Only verified email addresses appear in this drop-down menu. If you enabled email address privacy, then a no-reply will be the default commit author email address. For more information about the exact form the no-reply email address can take, see "Setting your commit email address." Screenshot of a GitHub pull request showing a drop-down menu with options to choose the commit author email address. octocat@github.com is selected. Below the commit message fields, decide whether to add your commit to the current branch or to a new branch. If your current branch is the default branch, you should

choose to create a new branch for your commit and then create a pull request. For more information, see "Creating a pull request." Screenshot of a GitHub pull request showing a radio button to commit directly to the main branch or to create a new branch. A new branch is selected.

➤ Click Commit changes or Propose changes.

### Launch of web app

To launch a Stream lit app using Git, follow these steps:

#### i. Create a Stream lit App:

Develop your Stream lit app and save it as a Python script (e.g., Home.py).

#### ii. Initialize a Git Repository:

Open a terminal in your project directory.

Run git init to initialize a new Git repository.

#### iii. Create a git ignore File:

Create a git ignore file to exclude unnecessary files (e.g., virtual environment folders, cache files).

Add entries like pycache/ and venv/ to the .git ignore file.

#### iv. Commit Your Initial Code:

Add your Stream lit app file and any other necessary files to the staging area using git add ..

Commit the changes with git commit -m "Initial commit".

#### v. Create a GitHub Repository:

Go to GitHub (<https://github.com/>) and create a new repository.

Follow the instructions to add a remote repository.

For example:

```
git remote add origin https://github.com/your-username/your-repo.git
git branch -M main
git push -u origin main
```

**vi. Deploy on Stream lit Sharing:**

Visit [Stream lit Sharing](https://www.streamlit.io/sharing) and log in with your Stream lit account.

Create a new app and connect it to your GitHub repository.

Specify the main Python script (e.g., app.py) as the entry point.

**vii. Configure Your Stream lit Sharing Settings:**

Adjust any necessary settings, such as environment variables or dependencies.

Save your changes.

**viii. Deploy Your App:**

Trigger the deployment process by clicking on the "Deploy" button in Stream lit Sharing.

**ix. Monitor Deployment:**

Monitor the deployment process and check for any errors or warnings.

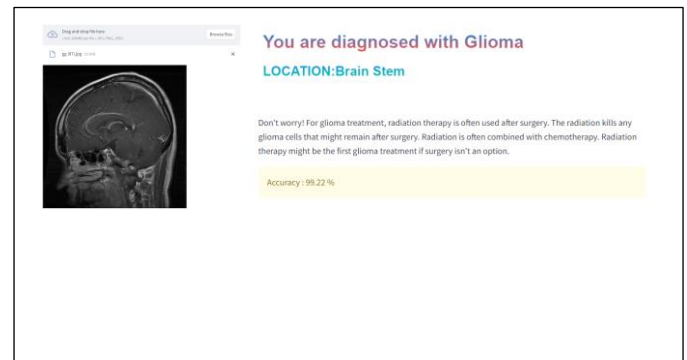
Once deployed successfully, you'll receive a link to your live Stream lit app.

**x. Update Your App:**

Make updates to your app as needed and push changes to your GitHub repository.

Stream lit Sharing will automatically redeploy your app with the latest changes.

providing precise information about its spatial location within the image. This dual functionality aims to assist medical professionals in swiftly and accurately diagnosing tumors, fostering a more efficient and informed decision-making process. Our approach contributes to the advancement of tumor identification methodologies while prioritizing user accessibility, ultimately enhancing the practicality and impact of our proposed solution in clinical settings.

**IV. RESULT**

In our proposed method, we employ Convolutional Neural Network (CNN) algorithms for the accurate classification and localization of various types of tumors within medical images. Our primary focus is on enhancing the precision and efficiency of tumor diagnosis. Through the utilization of CNNs, our model effectively learns intricate patterns and features within the image data, enabling it to discriminate between different tumor types with high accuracy. Additionally, our system is designed to deliver user-friendly outputs by not only identifying the type of tumor but also

**V. CONCLUSION**

A conclusion section is not required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions.

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