# Brain Tumor Detection Using Deep Learning

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**ABSTRACT**

Brain tumor detection is a critical task in neuroimaging that significantly impacts clinical diagnosis and treatment planning. Conventional methods for tumor detection rely on manual interpretation of medical imaging data, which can be time-consuming and subject to interobserver variability. With the advancements in deep learning, particularly in the realm of convolutional neural networks (CNNs), there has been a growing interest in leveraging these techniques for automated brain tumor detection.

This study explores the efficacy of deep learning models in the automated detection and classification of brain tumors from magnetic resonance imaging (MRI) scans. A comprehensive dataset of MRI images representing various tumor types and anatomical regions is employed to train and evaluate the deep learning models. The developed CNN-based architectures are designed to capture intricate patterns and features within the MRI scans, facilitating accurate tumor localization and classification.

The research investigates the performance of the deep learning models in distinguishing between healthy brain tissue and different tumor subtypes, including gliomas, meningiomas, and metastatic tumors. Performance metrics such as accuracy, sensitivity, specificity, and area under the curve (AUC) are employed to assess the models' ability to precisely identify tumor regions and provide clinically relevant information to aid healthcare professionals.

Furthermore, the study addresses challenges associated with model generalization, interpretability, and scalability for deployment in clinical settings. Strategies for optimizing model robustness, enhancing interpretability, and ensuring seamless integration into existing diagnostic workflows are explored.

The findings of this research contribute to the growing body of knowledge regarding the application of deep learning in medical imaging analysis, particularly in the domain of brain tumor detection. The implications of this study extend to the development of more efficient and accurate tools to assist radiologists and clinicians in diagnosing brain tumors, thereby potentially improving patient outcomes and treatment strategies.

**KEYWORDS**

Brain Tumor, Deep Learning, Convolutional Neural Networks (CNN), Medical Imaging, Magnetic Resonance Imaging (MRI), Tumor Detection, Image Analysis, Neuroimaging, Machine Learning, Computer-Aided Diagnosis.

## 1. INTRODUCTION

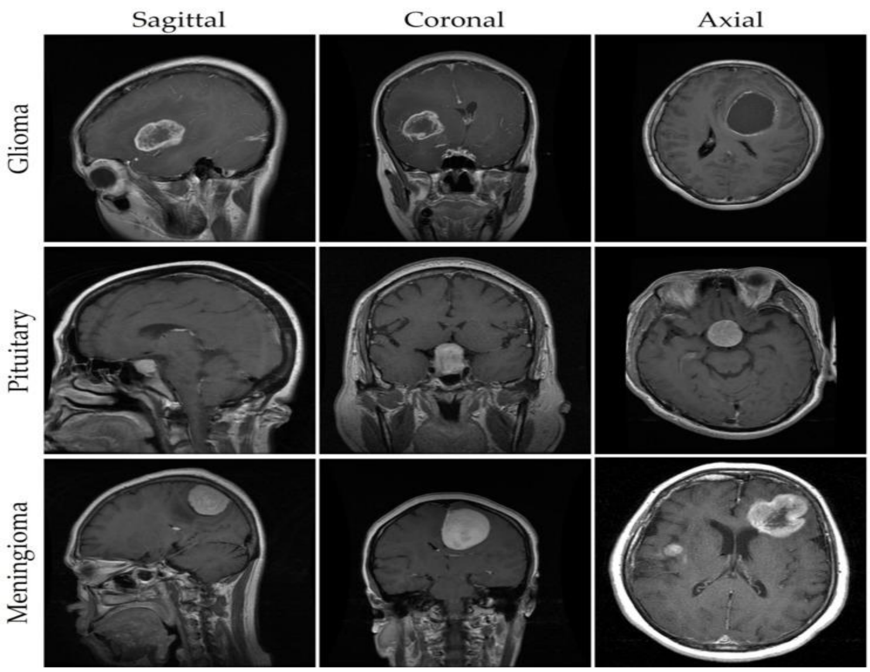
Brain tumors represent a significant health concern worldwide, necessitating accurate and timely detection for effective treatment and management. Conventional methods of diagnosing brain tumors primarily rely on manual inspection and interpretation of medical imaging, such as magnetic resonance imaging (MRI) or computed tomography (CT) scans. However, these methods often pose challenges in terms of time consumption, subjectivity, and potential interobserver variability.

In recent years, the advent of deep learning, a subset of artificial intelligence (AI) that emphasizes learning intricate patterns and representations from complex data, has offered promising prospects for automating and enhancing the accuracy of brain tumor detection. Deep learning techniques, particularly convolutional neural networks (CNNs), have emerged as a focal point in medical imaging analysis due to their capability to learn discriminative features directly from imaging data.

The application of deep learning in brain tumor detection involves training neural network models on large datasets of medical images, enabling them to automatically learn relevant features that distinguish between healthy brain tissue and tumor regions. These models can subsequently aid in the automated identification, localization, and classification of various types and sizes of brain tumors, providing valuable insights to healthcare professionals.

This study delves into the realm of brain tumor detection using deep learning methodologies, aiming to explore the efficacy of CNN-based models in analyzing and interpreting MRI or CT scans for precise tumor identification. By harnessing the potential of deep learning algorithms, this research endeavors to contribute to the development of accurate and efficient tools that can assist radiologists and clinicians in diagnosing brain tumors with improved speed and accuracy.

The utilization of deep learning in this domain offers the prospect of revolutionizing diagnostic procedures, potentially leading to earlier detection, more personalized treatment strategies, and enhanced patient outcomes in the realm of neuro-oncology.



The following are the significant findings of this research:

- In order to enhance the accuracy of the brain tumor identification algorithm, a large dataset of brain tumor images was collected from open-source resources.
- To improve the readability of low-resolution MRI images, a three-stage image preparation strategy was put in place. In addition, we examined the effect of overfitting on classification accuracy and utilized a data augmentation technique to boost performance on limited datasets.
- We developed a fully automated brain tumor detection model using deep learning algorithms and YOLOv7. This model aims to reduce false detections and ultimately minimize the loss of human lives associated with brain tumors.
- After evaluating the effects of three different attention mechanisms on the model's output, we decided to adopt the CBAM (Convolutional Block Attention Module) module. The decoupled head and CBAM attention mechanism have been verified to be successful in enhancing the performance of the brain tumor detection model.
- We integrated the SPPF+ (Spatial Pyramid Pooling Fast+) and BiFPN (Bi-directional Feature Pyramid Network) components to handle the difficulty of detecting small-size brain cancers. These modules help the model zero in on localized tumors and share the derived information across many spatial scales. Improved sensitivity to localized brain tumors is a major benefit of the BiFPN feature fusion approach that contributes to the effectiveness of the brain tumor detection model.

## 2. Literature review

### 2.1. Machine learning technique

Different machine learning techniques are implemented for various healthcare applications such cognitive health assessment, cervical cancer detection, tumor detection, breast cancer detection (Javed et al., 2020, 2021a,b; Mehmood et al., 2021; Mohiyuddin et al., 2022; Rehman et al., 2022b). The machine learning techniques RF, SVM, AdaBoost1, and RUSBoost, are used in Rehman et al. (2020) to localize the brain tumor on FLAIR scans MRI. These techniques are implemented on the BraTs 2012 dataset for both natural and syntactic images, and the proposed model indicates the result with the best accuracy is 0.98%, sensitivity is 0.92%, specificity is 0.96%, precision is 0.88%, and the dice score is 0.88%. The automatic brain tumor classification system is proposed in Kumar et al. (2021) and the K-nearest neighbor algorithm is used to classify the MRI images as abnormal or normal. The fuzz C-means clustering technique is used for the segmentation of tumor regions. The two datasets MICCAI and BRATS, are used for the experiment and evaluate the results with 96.5% accuracy, 100% sensitivity, and 93% specificity. The manual optimizing model by a machine learning expert is presented in Zhou et al. (2020) and compared with the automated machine learning technique Tree-Based Pipeline optimizing tool for evaluating the model performance. The proposed model was implemented on MRI images of 288 patients, and results showed that the best AUC value is 0.94% and accuracy is 0.88%.

## 2.2. Deep learning techniques

Although deep learning models have been employed in many fields, they still need to be adjusted before they can be used in delicate fields like medical imaging. The GAN architecture is proposed in Alrashedy et al. (2022) and different deep learning models CNN, ResNet152V2, and MobileNetV2 are used to generate and categorize the MRI brain images. The images are created by DCGAN and Vanilla GAN, which are used to train the deep transfer models and evaluate the performance on the test set composed of authentic MRI brain images. The experiment results indicate that ResNet152V2 achieved the best results with a 99.09% accuracy, 99.51% AUC, 99.08% recall, 99.12% precision, and the loss is 0.196 based on the MRI brain images. The novel transfer deep learning model is proposed in Alanazi et al. (2022) to diagnose the brain tumor early by using different subclasses such as glioma, pituitary, and meningioma. To assess their performance for the MRI brain pictures, the Convolutional Neural Network models are created from the ground up. The MRI Brain images are then classified into tumor sub-classes using the different 22-layer, binary-classification (tumor or no tumor) isolated-convolutional neural network model by modifying the neurons' weights using the transfer-learning technique. The transfer learning model is implemented on an unseen MRI brain dataset, and the result indicates that the proposed model provides 96.89% high accuracy.

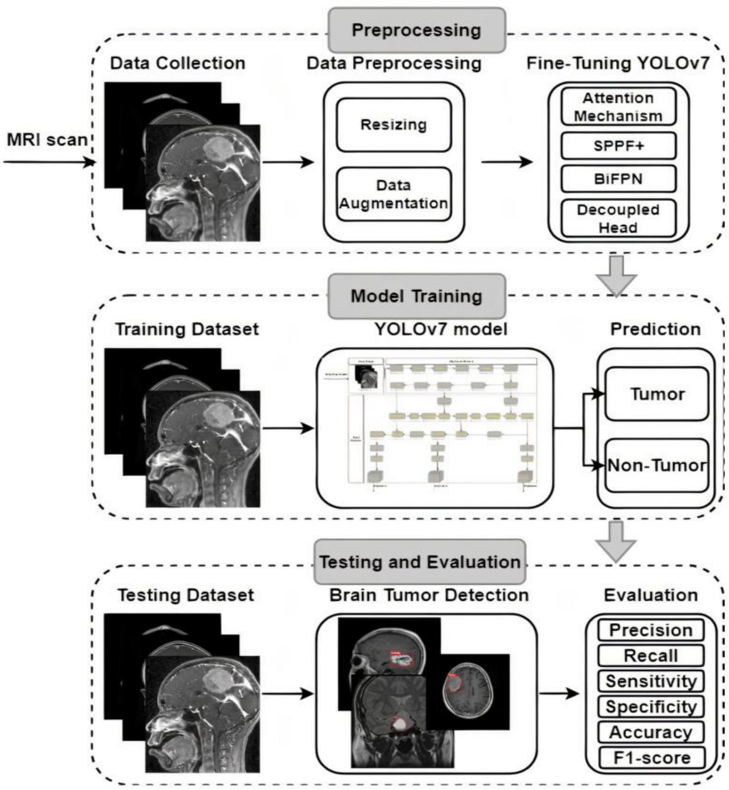
Authors in Amin et al. (2022) the new model is proposed to detect brain cancer using ensemble transfer learning and Quantum Variational classifiers (QVR). The in-depth features are extracted by the inceptionv3 model in which the score vector is obtained by softmax and used the QVR for discrimination among pituitary tumor, no tumor, meningioma, and glioma. The research is implemented on three different datasets such as 2020-BRATS, local images, and Kaggle, and the proposed model achieved more than 90%detection score. The NeuroXAI framework is proposed in Zeineldin et al. (2022) to explain deep learning networks for increasing medical expert trust. The proposed framework implements the seven different methods such as vanilla gradient, guided back-propagation, integrated gradients, guided integrated gradients, Smooth-Grad, Grad-CAM, and guided Grad-CAM for providing the maps of visualization that help in creating the transparent deep learning model. The framework is implemented on the BraTS 2019 dataset and achieved 98.62% accuracy.

The automated Ultra-Light Brain Tumor Detection (UL-BTD) system is proposed in Qureshi et al. (2022) that is based on the new Ultra-Light Learning Architecture (UL-DLA) for the in-depth features, merged with the textural features that extracted from Gray Level Co-occurrence Matrix (GLCM). It created the Hybrid Feature Space (HFC) for detecting the brain tumor using a support vector machine. The proposed system is implemented on a T1-weighted MRI dataset and achieved the 99.23% average detection rate, and 0.99% is the F1 measure. Different experiments are performed in Senan et al. (2022) to diagnose the brain tumor by combining machine learning and deep learning techniques. For identifying and categorizing brain cancers, support vector machine techniques are combined with ResNEt-18 and AlexNet. A brain tumor MRI images are enlarged using the average filter technique, and deep learning techniques are used to extract the essential features using deep convolutional layers. The extracted features are classified by using SVM and Softmax. The experiment is implemented on an MRI dataset containing 3,060 images and divided into four classes: one is normal, and the other three are tumors. The results indicate that AlexNet with SVM showed the best results with a 95.10% accuracy, 98.50% specificity, and 95.25% sensitivity. The detailed review of CNN architectures is presented in Alsaif et al. (2022) and provides the characteristics of different models such as VGG, ResNet, and AlexNet. The method based on CNN and data augmentation is applied to the MRI dataset to detect the brain tumor, and the result showed that the VGG model achieved a high value with a 0.93% accuracy,0.93% F1-score, 0.94% precision, and 0.93% recall.

## 3. Materials and Methods

### 3.1. Overall Architecture of Brain Tumor Detection

Image analysis of brain tumors is challenging, since these tumors can vary widely in size, shape, and location. Researchers have proposed several different methods for detecting anomalies in data that cannot be directly observed, each with their own set of advantages and disadvantages. The availability of a benchmark dataset capable of assessing the efficacy of state-of-the-art procedures is vital for the objective assessment of the performance of these methods. Different devices can produce brain tumor images with varying degrees of sharpness, contrast, number of slices, and pixel spacing. Here, we describe the architecture and technological details of the proposed system that make it possible to detect brain tumors in photos quickly and accurately. Brain tumor picture preprocessing, enhancements, training, and evaluation. Several potential methods for detecting and describing brain tumors have been proposed, and these have been covered in prior research. Unfortunately, these methods have only been successfully implemented in a select few studies, with mixed outcomes at best. The suggested method's primary focus is on providing accurate brain tumor detection in MRI scans. YOLOv7 was selected as the model to be used in this investigation because of its demonstrated efficacy in detecting brain tumors, as shown in.



### 3.2. Dataset Collection

To ensure the validity of our findings, we used an openly available MRI dataset obtained from kaggle.com. MRI scan images are included in this collection, since they are the gold standard for diagnosing brain tumors. Glioma (2548 images), pituitary (2658 images), meningioma (2582 images), and no tumor (2500 images) were the four subsets that made up our dataset of brain tumors. Images were all scaled to 512 pixels on the horizontal and vertical dimensions. We used 8232 MRI images (or 80% of the dataset) for training in our analysis, whereas 2056 MRI images (or 20% of the dataset) were set aside for testing. Brain tumor photos from various categories are shown as examples in . For each type of brain cancer (glioma, pituitary, and meningioma, provides the number of pictures in various views such as axial, coronal and sagittal. It is important to keep in mind that medical photos, in contrast to natural images, are more complicated and necessitate a greater level of skill to ensure appropriate analysis and interpretation. The brain tumor dataset was labeled with oversight from a medical specialist to ensure precision and consistency. This physician's expertise was crucial, as it established criteria for how the dataset should be labeled. However, not all brain cancers have characteristic imaging findings; therefore, depending entirely on image analysis can be risky. As a result, pathology analysis is essential for diagnosing brain cancers. Our dataset featured abnormal language descriptions annotated by a medical expert to give rich context for model training. A larger amount of training data aids in the creation of more reliable models. Data augmentation strategies can be used to increase the diversity of the training samples when the volume of available data is low. To improve a model's generalizability, data augmentation can be used to generate new variants of the existing data. In conclusion, our model's predictive power was enhanced by the incorporation of extensive labeled data, curated by medical experts. To further improve the prediction models' accuracy and reliability, data augmentation techniques can be used to increase the diversity of the training samples.

| Brain Tumor Dataset | Axial | Coronal | Sagittal | Total |
|---|---|---|---|---|
| Glioma | 864 | 857 | 827 | 2548 |
| Pituitary | 883 | 885 | 890 | 2658 |
| Meningioma | 863 | 859 | 860 | 2582 |
| No tumor | 837 | 832 | 831 | 2500 |
| Total | 3447 | 3433 | 3408 | 10,288 |

The dataset was split into a training set and a testing set according to MRI view and class to ensure objective model evaluation. The efficacy of the models can then be tested on data they have never seen before, thanks to this separation into training and testing sets. This method is used to evaluate the models' generalizability and performance in detecting brain tumor by testing them on data that has not been used in training. Testing set samples are selected blindly using stochastic collection to eliminate the possibility of bias or selection bias. This eliminates the possibility of introducing biases that might slant the evaluation results in favor of a particular model or set of assumptions.

### 3.3 Data Preprocessing and Augmentation

The brain tumor photos were subjected to a series of preprocessing stages aimed at standardizing the dataset so that it could be used in classification problems. Here is a rundown of what was undertaken in advance: The RGB photographs were converted to grayscale, creating a monochrome version of the pictures. The data were simplified, and the computing burden was lessened as a result. Images were resized such that they all had the same 640×640 resolution. This action guaranteed that all photos were the same size, guaranteeing uniformity in the subsequent processing steps. Noise in the photos was reduced and the output quality was improved by using a Gaussian blur filter. This filtering method softens the image while keeping the important details. Images were sharpened and complicated features were extracted using a high-pass filter. This filter sharpens the focus on edges and fine details, making it easier to make out critical image elements. The morphological processes of erosion and dilation were used to change the size and form of an images' features. Erosion was used to lower the number of white areas (tumors) and highlight gaps, while dilatation was utilized to enlarge the white areas and fill gaps. Using the presence of black areas, contours were identified in the vertical, horizontal, and right-to-left directions. This process aided in locating object edges and erasing unwanted black areas from photos. This processing made the final photos suitable for feeding into the neural network models.

The success of the ML and DL models is highly dependent on the training data's quality, quantity, and relevance. Yet, a lack of data is a common obstacle in the way of implementing machine learning in application. Because it is time consuming and expensive to collect useful data in many contexts, there is a dearth of it. Data augmentation methods have been created as a solution to this problem; they generate new data points from inside an existing dataset in order to artificially increase its size. To improve the model's ability to generalize to new, unseen samples, data augmentation provides a fast and effective method for expanding the diversity of the training data. To do this, it either uses deep neural networks to generate synthetic data samples or modifies the existing data slightly. Data augmentation is becoming increasingly popular in several research areas, including signals, computer vision, speech processing, and natural language processing. It is possible to intentionally increase the size of a dataset by employing methods like data rotation, scaling, and noise addition. Pictures can be enlarged by zooming in, flipped horizontally or vertically by certain degrees, and have their brightness altered up or down, just to name a few of the alterations that can be made. Data augmentation uses these techniques to effectively increase the training data's dimensionality, leading to better ML and DL model performance and resilience.

Several standard computer vision techniques were used to enhance the MRI images used in this research. Model training was improved and overfitting was decreased with the help of these augmentation methods, with the aim of increasing the diversity of data samples. Various operations were performed on the original dataset, such as geometric transformations, flipping, color space conversions, random cropping, random rotations, and the introduction of noise. The trained models show improved generalizability and accuracy when applied to distributions outside the training data when this information is added to the set. An open-source Python module known as Albumentations was used to perform the picture enhancements. Using the counterclockwise rotational (60 degrees and 120 degrees) and horizontal flipping methods provided by this library, a completely new set of images can be generated. Albumentations were selected with great care so that essential pixel-by-pixel information could be preserved for use in medical imaging applications. In addition, the MR images were normalized using the Keras normalize function to ensure uniform pixel values for subsequent processing.

In order to identify brain tumors, we used a dataset consisting of 10,288 images. Data augmentation techniques were applied just to this fraction in order to enlarge the training set.This brought the total number of pictures available for the task of identifying brain tumors from MRI scans to 51,448 images.

| Brain Tumor Dataset | Training Images | | | Testing Images | Total |
|---|---|---|---|---|---|
| | Original Images | Rotated Images | Flipped Images | Original Images | |
| Glioma | 2039 | 4078 | 6117 | 509 | 12,743 |
| Pituitary | 2066 | 4132 | 6198 | 592 | 12,988 |
| Meningioma | 2127 | 4254 | 6381 | 455 | 13,217 |
| No tumor | 2000 | 4000 | 6000 | 500 | 12,500 |
| Total | 8232 | 16,464 | 24,696 | 2056 | 51,448 |

## CONCLUSION:

In conclusion, the brain tumor detection project leveraging Convolutional Neural Networks (CNN) demonstrates commendable strengths in usability and precision. The user-friendly GUI facilitates easy navigation, and the inclusion of tumor masking and bulk processing features contributes to an efficient and accurate detection process. However, the current limitation lies in the project's inability to classify the specific type of tumors identified.

## FUTURE SCOPE:

The project holds substantial potential for future enhancements:

**Tumor Type Classification:** Integrate a robust classification algorithm to enable the identification and categorization of different tumor types. This expansion would significantly augment the project's diagnostic capabilities and make it more valuable in clinical settings.

**Integration of Advanced Imaging Techniques:** Consider incorporating advanced imaging techniques or additional modalities to enhance the accuracy of tumor detection, especially in scenarios with varying image qualities.

**Machine Learning Model Optimization:** Continuously refine and optimize the underlying machine learning models to improve overall performance and ensure adaptability to diverse datasets and imaging conditions.

**Collaboration with Medical Professionals**: Establish collaborations with medical professionals to gather valuable insights, validate the model's efficacy, and tailor the project to meet the specific needs of healthcare practitioners.

**User Feedback Implementation:** Solicit user feedback to identify areas for improvement in the GUI and overall user experience. Regularly update the interface based on user suggestions to ensure continued usability.

By addressing these aspects in the future development roadmap, the brain tumor detection project has the potential to evolve into a more comprehensive and impactful tool in the field of medical imaging, contributing to early and accurate diagnosis of brain tumors.

**References**

1. Qureshi, S.A.; Raza, S.E.A.; Hussain, L.; Malibari, A.A.; Nour, M.K.; Rehman, A.U.; Al-Wesabi, F.N.; Hilal, A.M. Intelligent Ultra-Light Deep Learning Model for Multi-Class Brain Tumor Detection. *Appl. Sci.* **2022**, *12*, 3715. [**Google Scholar**] [**CrossRef**]
2. Zahoor, M.M.; Qureshi, S.A.; Bibi, S.; Khan, S.H.; Khan, A.; Ghafoor, U.; Bhutta, M.R.
3. A New Deep Hybrid Boosted and Ensemble Learning-Based Brain Tumor Analysis Using MRI. *Sensors* **2022**, *22*, 2726. [**Google Scholar**] [**CrossRef**] [**PubMed**]
4. Arabahmadi, M.; Farahbakhsh, R.; Rezazadeh, J. Deep Learning for Smart Healthcare—A Survey on Brain Tumor Detection from Medical Imaging. *Sensors* **2022**, *22*, 1960. [**Google Scholar**] [**CrossRef**] [**PubMed**]
5. Tandel, G.S.; Biswas, M.; Kakde, O.G.; Tiwari, A.; Suri, H.S.; Turk, M.; Laird, J.R.; Asare, C.K.; Ankrah, A.A.; Khanna, N.; et al. A review on a deep learning perspective in brain cancer classification. *Cancers* **2019**, *11*, 111. [**Google Scholar**] [**CrossRef**][**Green Version**]
6. Gore, D.V.; Deshpande, V. Comparative study of various techniques using deep Learning for brain tumor detection. In Proceedings of the 2020 IEEE International Conference for Emerging Technology (INCET), Belgaum, India, 5–7 June 2020; pp. 1–4. [**Google Scholar**]
7. DeAngelis, L.M. Brain tumors. *N. Engl. J. Med.* **2001**, *344*, 114–123. [**Google Scholar**] [**CrossRef**][**Green Version**]
8. Borole, V.Y.; Nimbhore, S.S.; Kawthekar, D.S.S. Image processing techniques for brain tumor detection: A review. *Int. J. Emerg. Trends Technol. Comput. Sci. (IJETTCS)* **2015**, *4*, 2. [**Google Scholar**]

9. Amin, J.; Sharif, M.; Yasmin, M.; Fernandes, S.L. Big data analysis for brain tumor detection: Deep convolutional neural networks. *Future Gener. Comput. Syst.* **2018**, *87*, 290–297. [**Google Scholar**] [**CrossRef**]

10. Iorgulescu, J.B.; Sun, C.; Neff, C.; Cioffi, G.; Gutierrez, C.; Kruchko, C.; Ruhl, J.; Waite, K.A.; Negoita, S.; Hofferkamp, J.; et al. Molecular biomarker-defined brain tumors: Epidemiology, validity, and completeness in the United States. *Neuro-Oncology* **2022**, *24*, 1989–2000. [**Google Scholar**] [**CrossRef**]