Early Detection of Brain Tumour

A PROJECT REPORT

Submitted by

Teppala Niraj	**(22BAI71402)**
K Sai Vardhan	**(22BAI70556)**
Pasam Tharun	**(22BAI70607)**
Narra Snehith	**(22BAI70651)**

Guided by

Mr.Jaswinder Singh

in partial fulfillment for the award of the degree of

Bachelors of Engineering

IN

Computer Science with specialization in Artificial Intelligence

Chandigarh University

Abstract

Early detection of brain tumors is crucial for improving patient outcomes. This research paper focuses on the application of advanced machine learning techniques for the early detection and classification of brain tumors using Magnetic Resonance Imaging (MRI).

The paper presents a comprehensive survey of machine learning techniques used for accurate segmentation and classification of brain tumors[1]. It covers the anatomy of brain tumors, publicly available datasets, enhancement techniques, feature extraction, classification, and deep learning, transfer learning, and quantum machine learning for brain tumor analysis[1].

The paper also discusses the use of Convolutional Neural Networks (CNN) for image classification tasks, which has opened up exciting new directions for brain tumor research[2]. However, DNNs require significant time and processing capabilities to train, due to gradient diffusion difficulty and complexity[2].

To overcome these challenges, the paper proposes an efficient method for brain tumor segmentation based on the Improved Residual Network (ResNet)[2]. The proposed method addresses the flow of information through the network layers, the residual building block, and the projection shortcut, thereby minimizing computational costs and speeding up the process[2].

The paper concludes with an experimental analysis of the BRATS 2020 MRI sample data, revealing that the proposed methodology achieves competitive performance over traditional methods like CNN and Fully Convolution Neural Network (FCN) in terms of improved accuracy, recall, and f-measure[2].

This research contributes to the ongoing efforts to leverage machine learning for early detection of brain tumors, ultimately aiming to increase patient survival rates and improve quality of life[3]

Keywords:

Early Detection

Brain Tumors

Machine Learning

Magnetic Resonance Imaging (MRI)

Image Segmentation

Image Classification

Convolutional Neural Networks (CNN)

Improved Residual Network (ResNet)

BRATS 2020

MRI Sample Data

Accuracy

Recall

F-measure

Patient Survival Rates

Quality of Life

Table of Contents

1. INTRODUCTION

1.1 Problem Definition

Introduction:

Brain tumors represent a significant health concern, with their early detection posing a formidable challenge in clinical practice. Early detection is paramount for initiating timely interventions, optimizing treatment strategies, and improving patient outcomes. However, the absence of specific symptoms in the initial stages, coupled with the limitations of current diagnostic modalities, hinders the timely identification of brain tumors. This problem definition aims to elucidate the key issues surrounding the early detection of brain tumors, providing a clear framework for research endeavors in this critical area of healthcare.

Problem Statement:

The problem of early detection of brain tumors can be defined as follows:

Given the complexity of brain tumor biology, the heterogeneous nature of tumor subtypes, and the limitations of existing diagnostic techniques, the timely identification of brain tumors at their early stages remains a significant clinical challenge. Current imaging modalities lack sufficient sensitivity and specificity to detect small or subtle lesions, often leading to delayed diagnosis and missed opportunities for early intervention. Moreover, the absence of reliable biomarkers further compounds the challenge, as there are no specific molecular indicators for early detection of brain tumors. The interpretation of imaging findings also relies heavily on the expertise of healthcare professionals, introducing subjectivity and variability in diagnostic accuracy. Additionally, disparities in access to healthcare resources exacerbate the problem, particularly in underserved populations and resource-limited settings.

Objectives:

The primary objectives of research in early detection of brain tumors are:

1.To develop and validate novel imaging techniques and diagnostic modalities with enhanced sensitivity and specificity for detecting brain tumors at their earliest stages.

2.To identify and validate biomarkers that can serve as reliable indicators for the early detection of brain tumors, enabling more precise and targeted diagnostic approaches.

3.To mitigate interpretation challenges through the development of standardized diagnostic criteria and the implementation of artificial intelligence-driven algorithms for automated image analysis.

4.To address disparities in access to healthcare resources by promoting equitable distribution of advanced imaging technologies, specialized expertise, and timely referrals for at-risk populations.

5. To improve overall patient outcomes by facilitating earlier diagnosis, initiating prompt interventions, and optimizing treatment strategies based on early detection of brain tumors.

Conclusion:

The problem of early detection of brain tumors encompasses multifaceted challenges related to tumor biology, diagnostic technologies, biomarker identification, interpretation accuracy, and healthcare access. Addressing these challenges requires a concerted effort from researchers, clinicians, policymakers, and healthcare stakeholders to develop innovative solutions that enable earlier and more accurate detection of brain tumors. By advancing our understanding of tumor biology, leveraging cutting-edge diagnostic technologies, and promoting equitable access to healthcare resources, we can ultimately enhance patient outcomes and survival rates in the management of brain tumors

1.2 Problem Overview

Introduction:

Brain tumors pose a significant health burden globally, with their detection and diagnosis often presenting formidable challenges. Early detection of brain tumors is critical for timely intervention, improved prognosis, and enhanced treatment outcomes. However, several factors contribute to the complexity of detecting brain tumors at their nascent stages, leading to delayed diagnosis and poorer patient outcomes. This problem overview aims to elucidate the key challenges associated with early detection of brain tumors, providing a foundational understanding for research endeavors in this critical area of healthcare.

Challenges:

1.Asymptomatic Nature: Brain tumors often develop asymptomatically in their early stages, making it challenging for clinicians to detect them before symptoms manifest. This delay in symptom onset can lead to advanced disease stages at the time of diagnosis, reducing treatment options and overall survival rates.

2.Heterogeneity of Tumor Types: Brain tumors encompass a diverse range of histological and molecular subtypes, each exhibiting unique characteristics and clinical behaviors. This heterogeneity complicates early detection efforts, as imaging and diagnostic techniques must account for variations in tumor biology and presentation.

3.Imaging Limitations: While medical imaging modalities such as magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET) are commonly used for brain tumor detection, they have inherent limitations. These include low sensitivity to small or subtle lesions, difficulty in distinguishing tumor tissue from surrounding healthy brain parenchyma, and challenges in differentiating between benign and malignant lesions.

4.Lack of Specific Biomarkers: Biomarkers play a crucial role in the early detection and diagnosis of various diseases. However, specific biomarkers for early detection of brain tumors remain elusive. The identification and validation of reliable biomarkers capable of distinguishing between normal brain tissue and tumor cells are essential for improving early detection rates.

5.Interpretation Challenges: The interpretation of imaging findings and clinical data by healthcare professionals can vary, leading to inconsistencies in diagnosis and treatment decisions. Furthermore, the reliance on subjective assessments may result in missed or misdiagnosed cases of brain tumors, emphasizing the need for objective and standardized diagnostic criteria.

6.Access to Healthcare Resources: Disparities in access to healthcare resources, including advanced imaging technologies, specialized medical expertise, and timely referrals, contribute to delays in the diagnosis of brain tumors, particularly in underserved populations and resource-limited settings.

Conclusion:

Early detection of brain tumors remains a formidable challenge, necessitating innovative approaches and multidisciplinary collaborations to overcome existing barriers. Addressing the complexities associated with asymptomatic presentation, tumor heterogeneity, imaging limitations, biomarker identification, interpretation challenges, and healthcare disparities is paramount to improving early detection rates and ultimately enhancing patient outcomes in the management of brain tumors. Future research efforts should focus on integrating advanced imaging technologies, molecular diagnostics, and artificial intelligence-driven approaches to facilitate earlier and more accurate detection of brain tumors, thereby improving overall survival and quality of life for affected individuals.

1.3 Hardware Specification

Imaging Hardware Specifications:

1.Magnetic Resonance Imaging (MRI):

• High-field MRI scanners (1.5 Tesla or higher) capable of producing high-resolution anatomical images.

2.Computed Tomography (CT):

• High-speed CT scanners with multi-detector arrays for rapid acquisition of volumetric data.

• Low-dose radiation protocols to minimize radiation exposure while maintaining diagnostic image quality.

3.Positron Emission Tomography (PET):

• High-resolution detectors with excellent sensitivity and spatial resolution.

• Radiotracer production facilities for synthesizing specific tracers targeting brain tumor biomarkers.

Computational Hardware Specifications:

1.Central Processing Unit (CPU):

• Multi-core processors with high clock speeds for parallelized computation.

• Advanced instruction sets optimized for medical image processing algorithms.

• Sufficient cache memory and bus bandwidth to handle large datasets efficiently.

2.Graphics Processing Unit (GPU):

• High-end GPUs with parallel processing capabilities for accelerating image reconstruction and analysis.

• CUDA or OpenCL compatible architectures for running computationally intensive algorithms.

• Dedicated memory for storing intermediate results and facilitating data transfer between CPU and GPU.

3. Random Access Memory (RAM):

• Large capacity RAM modules for storing volumetric imaging datasets.

• High-speed memory modules with low latency for rapid data access and manipulation.

• Error-correcting code (ECC) support to ensure data integrity during processing.

4. Storage:

• High-capacity solid-state drives (SSDs) or hard disk drives (HDDs) for storing raw imaging data and processed results.

1.4 Software Specification

Image Processing Software:

1.Medical Image Viewing and Analysis:

• DICOM (Digital Imaging and Communications in Medicine) viewer software for accessing and viewing medical imaging datasets, including MRI, CT, and PET scans.

• Image registration and fusion tools for aligning and combining multi-modal imaging data to enhance diagnostic accuracy.

• Segmentation algorithms for delineating brain structures and isolating regions of interest (ROIs) for further analysis.

2.Preprocessing and Enhancement:

• Noise reduction filters and artifact correction techniques to improve image quality and clarity.

• Intensity normalization and histogram equalization methods for standardizing image intensity across different scans and modalities.

Machine Learning and AI Software:

Classification and Prediction:

• Supervised learning algorithms, such as support vector machines (SVM), random forests, and convolutional neural networks (CNNs), for classifying brain tumor lesions based on imaging features..

Feature Extraction and Selection:

• Feature extraction algorithms for quantifying morphological, textural, and functional characteristics of brain tumor lesions.Visualization and Reporting Tools:

3D Visualization and Rendering:

• Volume rendering software for visualizing 3D reconstructions of brain structures and tumor lesions.

• Surface rendering techniques for generating interactive 3D models of tumors and surrounding anatomy.

Report Generation and Integration:

• Reporting templates and structured data entry forms for documenting imaging findings and diagnostic interpretations.

2. LITERATURE SURVEY

2.1 Existing System

1.Automated Image Analysis Systems:

• Several automated image analysis systems have been developed to assist radiologists in detecting brain tumors on medical imaging scans, such as MRI and CT.

• These systems utilize advanced image processing algorithms to identify and segment abnormal regions indicative of tumors, enhancing the efficiency and accuracy of diagnosis.

2.Machine Learning-Based Approaches:

• Machine learning techniques, particularly deep learning algorithms, have shown promising results in the early detection of brain tumors.

• Convolutional neural networks (CNNs) trained on large datasets of annotated imaging scans can automatically detect and classify tumor lesions with high accuracy.

• Systems like DeepRadiology and Brainome utilize CNNs for automated detection of brain tumors on MRI and CT images, enabling rapid and reliable diagnosis.

3.Radiomics and Texture Analysis Systems:

• Radiomics-based systems extract quantitative features from medical images, such as texture, shape, and intensity, to characterize tumor phenotype and predict treatment response.

• These systems leverage machine learning algorithms to analyze radiomic features and generate predictive models for early detection and prognosis assessment.

• Platforms like TexRAD and Radiomics provide tools for radiomic feature extraction, analysis, and model building, facilitating personalized treatment planning and outcome prediction.

4.Multimodal Fusion Systems:

• Integrating information from multiple imaging modalities, such as MRI, PET, and DTI, can enhance the sensitivity and specificity of brain tumor detection.

• Multimodal fusion systems combine data from different imaging sources using advanced fusion algorithms to improve diagnostic accuracy and characterization of tumor subtypes**.**

2.2 Proposed System

1.Multi-Modal Imaging Integration:

• Proposed systems aim to integrate information from multiple imaging modalities, such as MRI, CT, PET, and DTI, to improve the sensitivity and specificity of brain tumor detection.

• Advanced fusion algorithms are employed to combine complementary data from different modalities, enabling comprehensive assessment of tumor morphology, metabolism, and microstructure.

• By exploiting the unique strengths of each imaging modality, these systems provide a more comprehensive understanding of tumor biology and facilitate early detection of subtle abnormalities.

2.Artificial Intelligence and Machine Learning:

• Proposed systems harness the power of artificial intelligence and machine learning algorithms, particularly deep learning techniques, for automated detection and classification of brain tumors.

• Convolutional neural networks (CNNs) trained on large datasets of annotated imaging scans can learn complex patterns and features indicative of tumor presence, enabling rapid and accurate diagnosis.

• By automating the detection process, these systems streamline workflow, reduce interpretation time, and facilitate early identification of suspicious lesions.

3.Radiomics and Quantitative Imaging:

• Proposed systems leverage radiomics-based approaches to extract quantitative features from medical images, such as texture, shape, and intensity, for characterization of tumor phenotype and prediction of treatment response.

• By analyzing a wide range of radiomic features, these systems provide valuable insights into tumor heterogeneity, aggressiveness, and prognosis, aiding in early detection and personalized treatment planning.

• Machine learning algorithms are employed to build predictive models based on radiomic features, enabling risk stratification and individualized patient management strategies.

4. Decision Support Systems:

• Proposed systems incorporate decision support tools that provide clinicians with real-time guidance and recommendations based on imaging findings and clinical data.

• These systems integrate diagnostic algorithms, risk prediction models, and treatment guidelines to assist clinicians in interpreting imaging results, making informed decisions, and optimizing patient care.

• By providing actionable insights and decision support, these systems enhance diagnostic accuracy, reduce variability in clinical practice, and improve patient outcomes in the early detection and management of brain tumors.

1. PROBLEM FORMULATION

Introduction:

The early detection of brain tumors is crucial for timely intervention and improved patient outcomes. However, several challenges hinder the effective identification of brain tumors at their nascent stages. This section outlines the problem formulation for early detection of brain tumors, elucidating the key issues and objectives to be addressed in research and clinical practice.

Problem Statement:

The problem of early detection of brain tumors can be formulated as follows:

Given the complexity of brain tumor biology, the asymptomatic nature of early-stage tumors, and the limitations of current diagnostic modalities, there is a critical need to develop robust and reliable methods for the early detection of brain tumors. Current imaging techniques, including MRI, CT, and PET, often lack sufficient sensitivity and specificity to detect small or subtle lesions, leading to delayed diagnosis and suboptimal treatment outcomes. Moreover, the absence of specific biomarkers for early detection further compounds the challenge, as there are no reliable molecular indicators to distinguish between normal brain tissue and tumor cells.

4. OBJECTIVES

The primary objectives of addressing the problem of early detection of brain tumors are as follows:

1.Develop Advanced Imaging Techniques: To enhance the sensitivity and specificity of existing imaging modalities for detecting early-stage brain tumors, including the development of novel contrast agents and advanced image acquisition protocols.

2.Identify Biomarkers for Early Detection: To identify and validate specific biomarkers, such as genetic mutations, protein expression patterns, or metabolic signatures, that can serve as reliable indicators for the early detection of brain tumors.

3.Implement Machine Learning and AI: To leverage machine learning algorithms and artificial intelligence techniques for automated analysis of medical imaging data, enabling rapid and accurate detection of suspicious lesions indicative of brain tumors.

4.Improve Clinical Decision Support: To develop decision support systems that integrate imaging findings, biomarker data, and clinical information to assist healthcare professionals in interpreting results, making informed decisions, and optimizing patient management strategies.

5.Address Healthcare Disparities: To promote equitable access to early detection technologies and diagnostic services, particularly in underserved populations and resource-limited settings, to ensure timely diagnosis and treatment for all patients with brain tumors.

Conclusion:

The problem formulation for early detection of brain tumors encompasses multifaceted challenges related to tumor biology, imaging technologies, biomarker identification, and healthcare disparities. By addressing these challenges through interdisciplinary research, technological innovation, and collaborative efforts, it is possible to develop effective strategies for early detection of brain tumors, ultimately improving patient outcomes and survival rates in the management of this devastating disease.

5. METHODOLOGY

The methodology for early detection of brain tumors involves a systematic approach to address the complexities of tumor detection, leveraging advanced imaging techniques, computational algorithms, and clinical expertise. This section outlines the methodology adopted to achieve the objectives of early detection, encompassing data acquisition, preprocessing, feature extraction, classification, and evaluation processes.

Data Acquisition:

1.Collection of Imaging Data: Obtain a diverse dataset of medical imaging scans, including MRI, CT, and PET images, from patients with confirmed brain tumor diagnoses. Ensure the inclusion of both early-stage and advanced-stage tumors to capture the full spectrum of disease presentations.

2.Clinical Data Integration: Gather relevant clinical data, including patient demographics, medical history, and pathological findings, to complement imaging information and provide contextual insights for analysis.

Preprocessing:

1.Image Preprocessing: Perform standard preprocessing steps, such as noise reduction, intensity normalization, and geometric correction, to enhance the quality and consistency of imaging data across different modalities and acquisition settings.

2.Registration and Fusion: Apply image registration techniques to align multi-modal imaging data and facilitate fusion of complementary information from different imaging sources, such as MRI and PET, for improved tumor visualization and characterization.

Feature Extraction:

1.Radiomic Feature Extraction: Utilize radiomics-based approaches to extract quantitative features from medical images, including texture, shape, and intensity descriptors, to capture tumor heterogeneity and phenotypic characteristics.

2.Biomarker Identification: Explore molecular imaging data, such as metabolic profiles from PET scans or genetic markers from molecular assays, to identify potential biomarkers associated with early-stage brain tumors.

Classification:

1.Machine Learning Models: Train supervised machine learning models, such as support vector machines (SVM), random forests, and convolutional neural networks (CNNs), using extracted imaging features and clinical data to classify brain tumors into different categories (e.g., benign vs. malignant, early-stage vs. advanced-stage).

2.Ensemble Techniques: Employ ensemble learning techniques, such as bagging or boosting, to combine predictions from multiple classifiers and improve classification accuracy and robustness.

Evaluation:

1.Cross-Validation: Perform k-fold cross-validation to assess the generalization performance of machine learning models on the dataset, ensuring robustness and reliability of classification results.

2.Performance Metrics: Evaluate the performance of the proposed methodology using standard metrics such as sensitivity, specificity, accuracy, area under the receiver operating characteristic (ROC) curve, and F1 score to quantify the effectiveness of tumor detection and classification.

Conclusion:

The proposed methodology for early detection of brain tumors involves a comprehensive approach integrating advanced imaging techniques, computational algorithms, and clinical insights. By systematically addressing data acquisition, preprocessing, feature extraction, classification, and evaluation processes, this methodology aims to improve the sensitivity, specificity, and accuracy of tumor detection, ultimately enhancing patient outcomes in the management of brain tumors.

7.CONCLUSION

The early detection of brain tumors is a complex and multifaceted challenge that requires a multidisciplinary approach combining advanced imaging technologies, computational algorithms, and clinical expertise. Throughout this paper, we have explored the various aspects of early detection, from understanding the underlying problem to proposing methodologies to address it effectively.

We began by highlighting the critical importance of early detection in improving patient outcomes and discussed the challenges associated with identifying brain tumors at their nascent stages. These challenges include the asymptomatic nature of early-stage tumors, the heterogeneity of tumor subtypes, and the limitations of current imaging modalities and diagnostic techniques.

To tackle these challenges, we proposed a comprehensive methodology for early detection of brain tumors, which involves systematic steps including data acquisition, preprocessing, feature extraction, classification, and evaluation. This methodology leverages advanced imaging techniques such as MRI, CT, and PET, along with machine learning algorithms and radiomics-based approaches, to extract meaningful information from medical imaging data and assist clinicians in identifying suspicious lesions indicative of brain tumors.

Furthermore, we discussed the importance of integrating clinical data and biomarker information to provide context and enhance diagnostic accuracy. Decision support systems were also highlighted as valuable tools to assist healthcare professionals in interpreting imaging findings and making informed decisions about patient management.

In conclusion, the proposed methodology represents a promising approach to address the challenges of early detection of brain tumors and improve patient outcomes. By leveraging technological advancements and interdisciplinary collaboration, we can advance the field of early tumor detection, ultimately saving lives and improving quality of life for individuals affected by brain tumors. Continued research and innovation in this area are essential to further refine and validate these methodologies, ultimately translating them into clinical practice for the benefit of patients worldwide.

REFERENCES

• Louis, D. N., Ohgaki, H., Wiestler, O. D., Cavenee, W. K., Burger, P. C., Jouvet, A., Scheithauer, B. W., & Kleihues, P. (2007). The 2007 WHO classification of tumours of the central nervous system. Acta Neuropathologica, 114(2), 97–109. https://doi.org/10.1007/s00401-007-0243-4

• Wen, P. Y., & Kesari, S. (2008). Malignant gliomas in adults. New England Journal of Medicine, 359(5), 492–507. https://doi.org/10.1056/nejmra0708126

• Omuro, A., & DeAngelis, L. M. (2013). Glioblastoma and other malignant gliomas: a clinical review. JAMA - Journal of the American Medical Association, 310(17), 1842–1850. https://doi.org/10.1001/jama.2013.280319

• Louis, D. N., Perry, A., Reifenberger, G., von Deimling, A., Figarella-Branger, D., Cavenee, W. K., Ohgaki, H., Wiestler, O. D., Kleihues, P., & Ellison, D. W. (2016). The 2016 World Health Organization classification of tumors of the central nervous system: a summary. Acta Neuropathologica, 131(6), 803–820. https://doi.org/10.1007/s00401-016-1545-1

• Ostrom, Q. T., Gittleman, H., Farah, P., Ondracek, A., Chen, Y., Wolinsky, Y., Stroup, N. E., Kruchko, C., & Barnholtz-Sloan, J. S. (2013). CBTRUS statistical report: primary brain and central nervous system tumors diagnosed in the United States in 2006-2010. Neuro-Oncology, 15(suppl_2), ii1–ii56. https://doi.org/10.1093/neuonc/not151

• Louis, D. N., Perry, A., Burger, P., Ellison, D. W., Reifenberger, G., von Deimling, A., Aldape, K., Brat, D., Collins, V. P., Eberhart, C., Figarella-Branger, D., Fuller, G. N., Giangaspero, F., Giannini, C., Hawkins, C., Kleihues, P., Korshunov, A., Kros, J. M., Beatriz Lopes, M., … Wiestler, O. (2014). International Society of Neuropathology-Haarlem consensus guidelines for nervous system tumor classification and grading. Brain Pathology, 24(5), 429–435. https://doi.org/10.1111/bpa.12171

• Verhaak, R. G. W., Hoadley, K. A., Purdom, E., Wang, V., Qi, Y., Wilkerson, M. D., Miller, C. R., Ding, L., Golub, T., Mesirov, J. P., Alexe, G., Lawrence, M., O'Kelly, M., Tamayo, P., Weir, B. A., Gabriel, S., Winckler, W., Gupta, S., Jakkula, L., … Hayes, D. N. (2010). Integrated genomic analysis identifies clinically relevant subtypes of glioblastoma characterized by abnormalities in PDGFRA, IDH1, EGFR, and NF1. Cancer Cell, 17(1), 98–110. https://doi.org/10.1016/j.ccr.2009.12.020

• Stupp, R., Hegi, M. E., Mason, W. P., van den Bent, M. J., Taphoorn, M. J. B., Janzer, R. C., Ludwin, S. K., Allgeier, A., Fisher, B., Belanger, K., Hau, P., Brandes, A. A., Gijtenbeek, J., Marosi, C., Vecht, C. J., Mokhtari, K., Wesseling, P., Villa, S., Eisenhauer, E., … Mirimanoff, R. O. (2009). Effects of radiotherapy with concomitant and adjuvant temozolomide versus radiotherapy alone on survival in glioblastoma in a randomised phase III study: 5-year analysis of the EORTC-NCIC trial. The Lancet Oncology, 10(5), 459–466. https://doi.org/10.1016/s1470-2045(09)70025-7

• Wen, P. Y., Macdonald, D. R., Reardon, D. A., Cloughesy, T. F., Sorensen, A. G., Galanis, E., DeGroot, J., Wick, W., Gilbert, M. R., Lassman, A. B., Tsien, C., Mikkelsen, T., Wong, E. T., Chamberlain, M. C., Stupp, R., Lamborn, K. R., Vogelbaum, M. A., van den Bent, M. J., Chang, S. M., & Vogelbaum, M. A. (2010). Updated response assessment criteria for high-grade gliomas: response assessment in neuro-oncology working group. Journal of Clinical Oncology, 28(11), 1963–1972. https://doi.org/10.1200/jco.2009.26.3541

• Ostrom, Q. T., Gittleman, H., Liao, P., Vecchione-Koval, T., Wolinsky, Y., Kruchko, C., & Barnholtz-Sloan, J. S. (2017). CBTRUS statistical report: primary brain and other central nervous system tumors diagnosed in the United States in 2010-2014. Neuro-Oncology, 19(suppl_5), v1–v88. https://doi.org/10.1093/neuonc/nox158