The Gulf Journal of Oncology

Indexed By PubMed and Medline Database

Issue 50, Jan. 2026
ISSN No. 2078-2101



The Official Journal of the Gulf Federation For Cancer Control

Table of Contents

Original Articles:

The impact of mental toughness training program on psychological well–being and resilience in cancer patients: A Randomized Controlled Trial **07**
Negin Hemmati, Kourosh Zarea. Samira Beiranvand, Saeed Ghanbari, Mehran Hosseinzadeh

Neuro–oncology Burden in Developing Countries: A Retrospective Cost–Analysis Study **19**
Said Nassier Said Alsenani, Rawan Nasser Almaskari, Yusra Abid Shah, Balqees Yousuf Hussain Al Mujaini, Alshifa Khalifa Alsaidi, Maryam Saud Mohammed AlBalushi, Fatema Dawood Mulla Hasan Almualem, Tariq Al–Saadi

Prospective observational comparative study of radiotherapy induced toxicities (xerostomia, skin reaction, and mucositis) between three–dimensional conformal radiotherapy and intensity modulated radiotherapy technique to oral cavity cancer of head and neck. **28**
Dr. Mhendr Dhakar, Dr. Hameeduzzafar Ghori, Dr. Atal Singh Parihar, Dr. Raju Prajapati, Dr. Om Prakash Singh, Dr. Vineeta Yogi, Dr. Vivek Tiwari, Dr. Rakesh Mahawar, Dr. Tushar Jassal

Epidemiological characteristics, prognostic factors, and survival of resectable colorectal cancer in a Moroccan population **36**
Rachid El Jim, Yousra.El Kirami, Laila.Chbani, Hind.Mrabti, Adil.Najdi, Karima. El Rhazi, Naoufel.Mellas, Ghizlane. Kharrasse. Said.Afkir, Khalid. Maazaz, Mohammed. El Abkari, Sidi Adil. Ibrahimi, Nada.Lahmidani

A Prospective Study Comparing Treatment Outcomes of Brentuximab Vedotin Plus AVD versus ABVD in Egyptian Patients with Advanced Classical Hodgkin Lymphoma **47**
Marwa N. Omar, Zeinab M. Elsayed, Rania M. Afify, Nervana M. Hussien, Haytham A. Abdelkader

Factors Influencing Breast Cancer Survival Outcomes in the Central Region of Saudi Arabia **56**
Amen Bawazir, Sadeem Alhalafi, Abdulrahman Jazieh, Wasif Ali Khan, Rumaisa Ali Khan

Assessing the use of anti–PD–1/PD–L1 cancer therapies in the Middle Eastern Country of Lebanon: a single–center study **65**
Reem El Hindi, Salim Moussa

Review Articles:

Artificial Intelligence Applications in Prognosis and Treatment of Neuro–oncology: A review **70**
Adham Al–Rahbi, Tariq Al–Habsi, Tariq Al–Saadi

Case Reports:

Lower Gastrointestinal Bleeding Revealing an Early–Stage Primary Anorectal Melanoma: A Case Report **87**
Hanane Aksim, Faisal El mouhafid, Mohamed Kaakoua, Meryem Belhamdiya, Ismail Essadi, Rachid El barni, Rachid Akka

Development of spontaneous subcutaneous emphysema in a case of squamous cell carcinoma of right lung during radiotherapy treatment a rare instance **92**
Dr Prarabdh Singh, Dr Arjun Agarwal, Dr Aditi Singh, Dr Siddharth Arora, Dr Kirti Arora, Dr Ankit Tebrawal

Conference Highlights/Scientific Contributions

- **News Notes** **96**
- **Advertisements** **99**
- **Scientific Activities** **101**

Review Article

Artificial Intelligence Applications in Prognosis and Treatment of Neuro–oncology: A review

Adham Al–Rahbi[1], Tariq Al–Habsi[2], Tariq Al–Saadi[3,4]

[1]Anatomical pathology program, Oman Medical Specialty Board, Al–khoudh, Muscat 132, Oman, E–mail: 123090adham1@gmail.com.
[2]Radiology Residency Program, Oman Medical Specialty Board, Al–Khoudh, Muscat 132, Oman.
[3]Department of Neurosurgery, Khoula Hospital, Muscat 123, Sultanate of Oman.
[4]Department of Neurosurgery – Cedars–Sinai Medical Center, 8700 Beverly Blvd, Los Angeles, CA 90048

Abstract:

Introduction: Artificial intelligence (AI) is the general term that contains Machine Learning (ML), and Deep Learning (DL). Utilization of these technologies in brain tumor treatment and prognosis is promising.

Aim: This article aims to review recent applications of AI in neuro–oncology treatment and prognosis. Furthermore, it elucidates the challenges and future directions.

Method: A comprehensive literature review in four databases (Wiley, Scopus, PubMed, and Google Scholar) gave a total of 21 articles using AI in neuro–oncology treatment and disease prognosis. papers were grouped and reviewed. The data was summarized and presented in tables and graphs. This is the first article to review these two areas of AI in neuro–oncology in a single paper and provide insight into knowledge gaps and future directions.

Results: Most of the reviewed articles are about prognosis (14 articles). The largest article in sample size (41222) is about the prediction of inpatient Length of Stay (LOS) after brain tumor surgery. They used twenty–nine machine learning algorithms. In articles about the treatment of neuro–oncology, the highest sample size is (1585) in assessment of treatment response using AI algorithms.

Conclusion: AI technologies implementation in neuro–oncology is crucial. More research and validation of current applications is needed. And careful integration of these technologies is important.

Keywords: Artificial intelligence (AI), Machine Learning (ML), Deep Learning (DL), Neuro–oncology, Neurosurgery, Treatment, Prognosis.

Abbreviations:
Artificial intelligence (AI)
Artificial Neural Network (ANN)
Central Nervous System (CNS)
Computed Tomography (CT)
Convolution Neural Network (CNN)
cycle–Generative Adversarial Networks (cycle–GANs)
Deep Learning (DL)
Food and Drug Association (FDA)
Gaussian Mixture Model (GMM)
Generalized Additive Method (GAM)
High–Resolution Magic Angle Spinning Nuclear Magnetic Resonance (HRMAS NMR)
Length Of Stay (LOS)
Machine Learning (ML)
Magnetic Resonance Imaging (MRI)
O–(2–[18F]FluoroEthyl)–L– Tyrosine Positron–Emission Tomography (FET PET)
Overall Survival (OS)
Progression-Free Survival (PFS)
Surface–Enhanced Raman scattering (SERS)
The area under the curve (AUC)
Time–Activity Curves (TAC)

Introduction:

The computer's ability to perform problem–solving activities and complex tasks that require higher intelligence is referred to the term Artificial Intelligence (AI). AI is a broad term consisting of Machine Learning (ML) which itself includes Deep Learning (DL) [(1)]. ML is a group of algorithms that allow the computer to learn from

Corresponding author: Dr.Tariq Al–Saadi, MD, MSc Department of Neurosurgery, Khoula Hospital, Muscat 123, Sultanate of Oman. Department of Neurosurgery – Cedars–Sinai Medical Center, 8700 Beverly Blvd, Los Angeles, CA 90048 Email: t.dhiyab@hotmail.com tariq.al–saadi@mail.mcgill.ca

the repetition of experience by pattern identification to make an appropriate decision. DL is the use of multilayers of artificial neural networks to analyze the offered data and extract features from images and voices.

Central Nervous System (CNS) tumors classified into primary and secondary are rare types of tumors but have a significant impact on global health. Annually there are more than 250000 reported cases of neuro–oncological tumors. 72.98% of brain tumors didn't achieve successful treatment and ended in death in the high–income and upper–middle–income countries. [2] Glioma is the most common intracranial tumor that arises from glial cells in the brain or spinal cord.

AI integration in neuro–oncology shows promise. It transforms the medical field in various stages starting from patient triaging, to assisting with tumor diagnosis, grading, and making personalized treatment plans. Additionally, it predicts the patient's prognosis and monitors disease progression.

Prediction of the prognosis of certain brain tumors is challenging. AI is applied in the prediction of brain tumors in various ways for example it is used to predict the inpatient Length Of Stay (LOS), predict tumor growth, predict patient survival, and predict brain tumor metastasis after gamma knife radiosurgery. Additionally, researchers used deep radiomics features or specific immune cell markers to predict the survival of brain tumor patients. With the new advances in AI, it can predict the seizure risk with a brain tumor and predict motor area activation before brain surgery using the neural network method by analyzing presurgical functional MRI images. Despite all the advances in prediction models they were found to lack integral elements in their development and methodology according to a systematic review including sixty–two publications with more than 150 prediction models [3].

Brain tumor treatment consists of different stages and steps. AI is implemented in most of the steps to enhance overall management outcomes. ML and DL demonstrate a significant potential in the treatment of brain tumors. It assists surgical and non–surgical therapy, plans radiotherapy doses, accurately assesses intraoperatively, and monitors recurrence. AI transforms therapy of brain tumors by introducing personalized therapy, especially in those rare types of brain tumors.

Certain articles reviewed AI applications in brain tumor classification, and diagnosis [29]. However, up to the authors knowledge, this is one of the first reviews discussing AI applications in treatment and prognosis of neuro–oncology in a single paper and provide insight into knowledge gaps and future directions.

Method:

The aim of this review is to study the trends of AI use in the treatment and prognosis of neuro–oncology. To achieve this goal a comprehensive search was conducted in multiple electronic databases including (Wiley, Scopus, Google Scholar, and PubMed) published from inception till June 2023. The keywords used were Artificial intelligence, Machine learning, Deep learning, radiomics, neurosurgery, treatment, therapy, prognosis, prediction, and neuro–oncology. The articles were retrieved, screened, duplicates deleted, and categorized into two main categories treatment and prognosis. Articles were then summarized, and tables are made. Two independent reviewers (A.R. and T.H.) performed the search. Any disagreements during the selection process were resolved by (T.S.) to maintain objectivity and consistency. The Preferred Reporting Items for Systematic Reviews and Meta–Analyses (PRISMA) were followed and shown in **Figure 1.** Inclusion criteria involved articles discussing AI in neuro–oncology treatment and prognosis prediction that were published in English as full–text, original research articles, and review articles. The excluded articles include abstracts only**,** letters to the editor, commentary, and non–English articles. This type of study did not require approval from research ethics committee. The recent advances in the treatment and prognosis of neuro–oncology and possible applications of AI were summarized. Furthermore, challenges and future directions in the application of such models in the field were presented.

Results:

The comprehensive search in the above electronic databases yielded 21 articles that follow the inclusion criteria. The highest countries with published research on AI in neuro–oncology prognosis and treatment are USA, Germany, and Italy, respectively. **Figure 2 shows more details about publications in this field per country.** Galldiks, N. is found to be the highest publishing author in this field. **Figure 3 shows the authors with the highest publications using AI in neuro–oncology prognosis and treatment**. Most authors in this research area are affiliated with the Jülich Research Center, Cologne University and Hospital which are all located in Germany. **Figure 4 shows the top ten affiliations searching AI in neuro–oncology prognosis and treatment.** Generally, glioma is found to be the most commonly studied brain tumor and is mentioned frequently in different applications of AI.

The prognosis of neuro–oncology tumors is found in fourteen articles. The highest sample size is 41222 which is found in Muhlestein and colleagues article, that

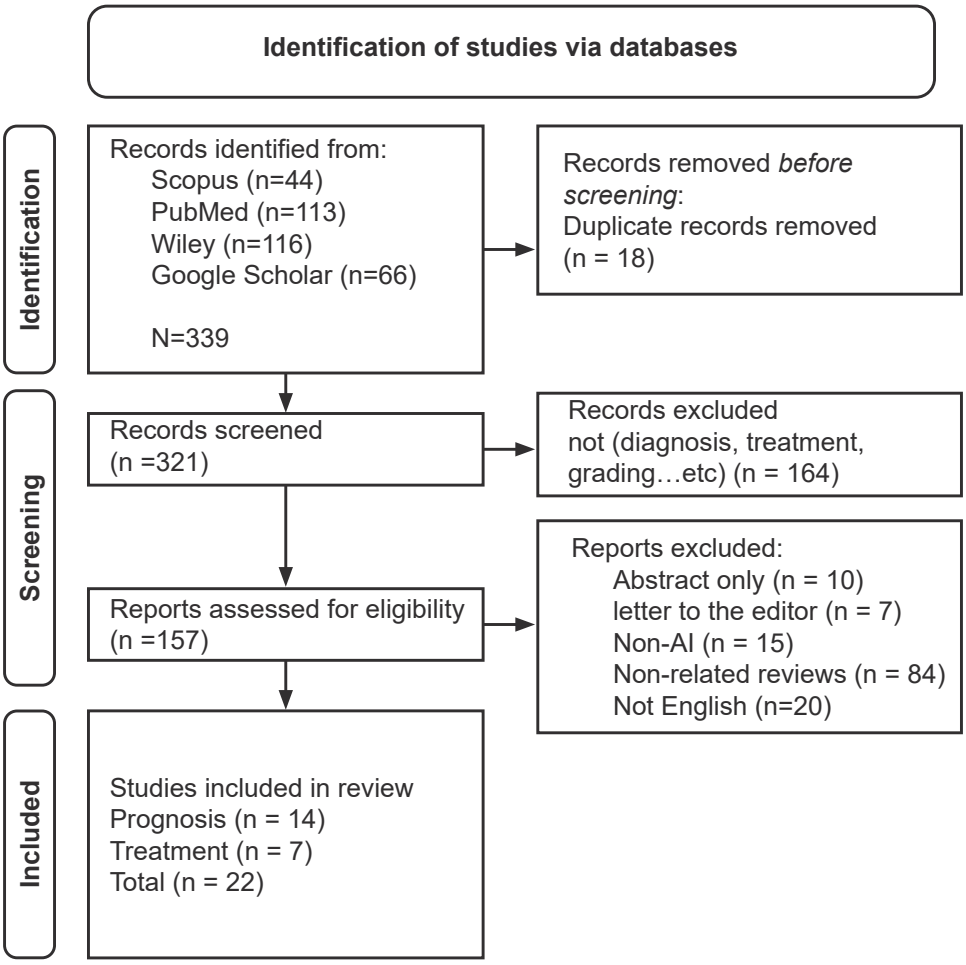


Figure 1: The Preferred Reporting Items for Systematic Reviews and Meta–Analyses (PRISMA).

From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71. For more information, visit: http://www.prisma–statement.org/

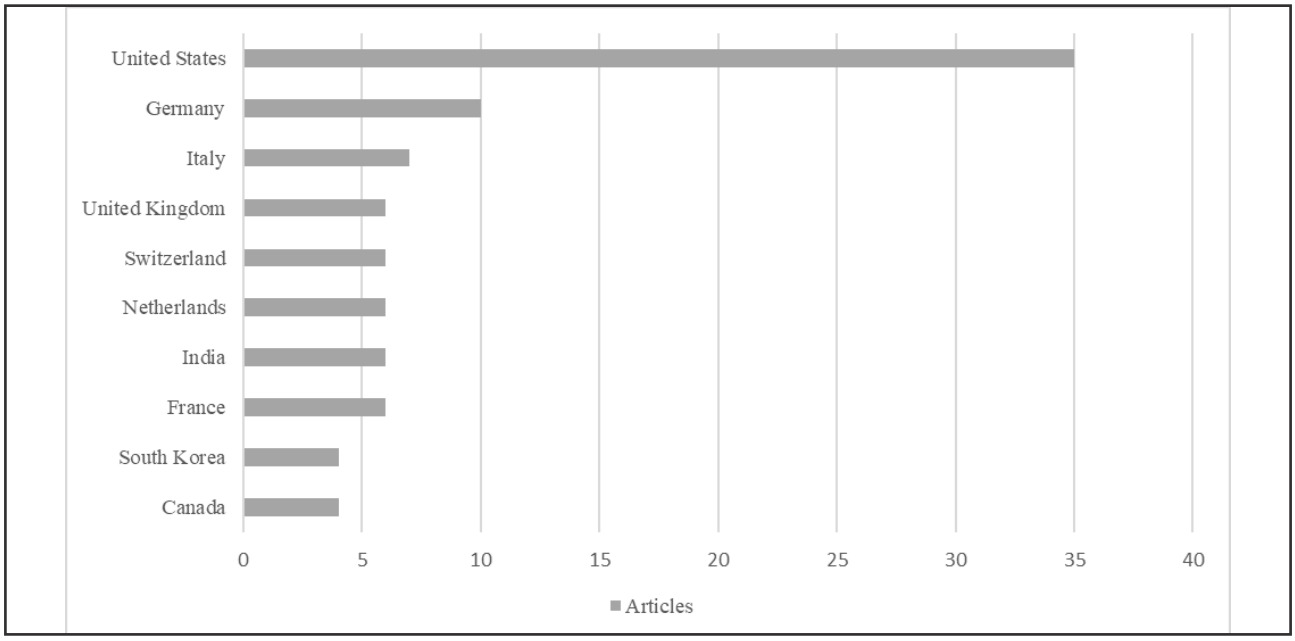


Figure 2: Number of publications per country searching AI in neuro–oncology prognosis and treatment.

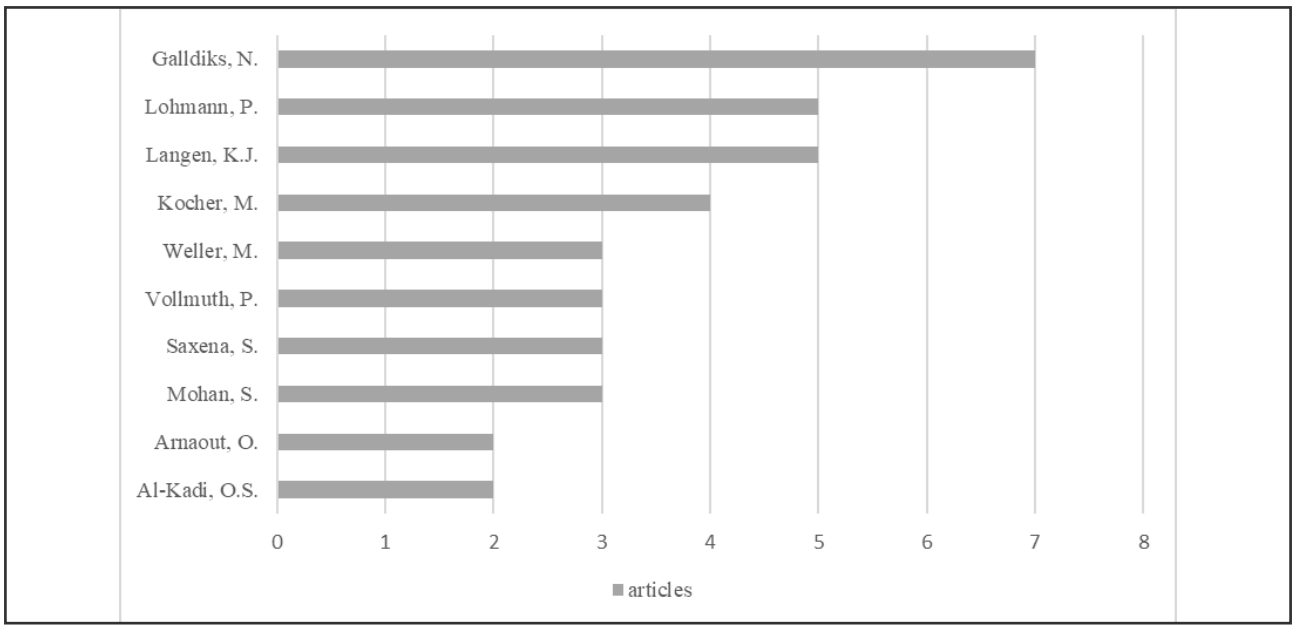


Figure 3: Authors with the highest publications using AI in neuro–oncology prognosis and treatment.

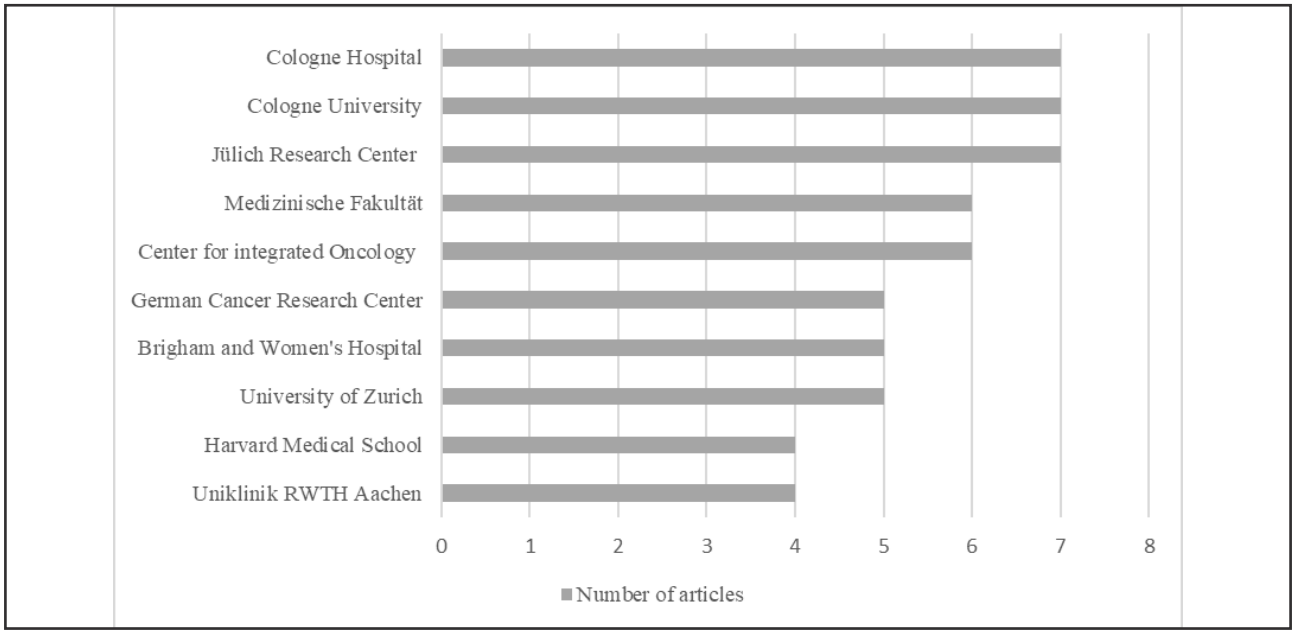


Figure 4: Top ten affiliations searching AI in neuro–oncology prognosis and treatment.

predicts Inpatient Length of Stay (LOS) after brain tumor surgery [4]. It is the highest among all articles included in this paper as they used twenty–nine machine learning algorithms. Table 1 shows the articles discussing AI in neuro–oncology prognosis.

AI–based **treatment** in neuro–oncology is discussed in eight articles. The highest sample size is 1585 for the assessment of tumor response to treatment in Jayachandran Preetha and colleagues' article [5]. Table 2 includes the articles discussing AI in neuro–oncology treatment. AI in the treatment of neuro–oncology is integrated to enhance overall management outcomes, radiotherapy guidance, aid treatment planning, surgical management assistance, and detection of progression after treatment.

Prognosis

Predict the inpatient LOS:

ML has been used widely in neuro–oncology prognosis. A group of researchers proposed a model **to predict the inpatient LOS** after a craniotomy for a brain tumor [4]. They identified 29 ML algorithms and evaluated

No	Study title	Sample size	AI use (prognosis, diagnosis, treatment)	Modality used	Tumor type	Tumor grading	Validation method (yes/ no) if yes what method	Precision (Area under the curve)	Accuracy	Recommendation	Future direction/ Important method
1.	Improving personalized tumor growth predictions using a Bayesian combination of mechanistic modeling and machine learning	500	prognosis	the Bayesian coupling of mathematical modeling and machine learning,	Glioma, chronic lymphocytic leukemia (CLL), and ovarian cancer	N/M	N/M	N/M	N/M	the combination of machine learning and mathematical modeling approaches can lead to accurate predictions of clinical outputs in the context of data sparsity and limited knowledge of disease mechanisms.	to propose an adequate mathematical model that describes the dominant dynamics of the disease. Also, introducing density estimation methods to be able to integrate categorical variables would greatly benefit the technique, especially in biomedical problems (e.g., it would be extremely beneficial to include the grade of a tumor, or the particular sequence of therapies that a patient has undergone).
2.	Machine learning may predict individual hand motor activation from resting–state fMRI in patients with brain tumors in perirolandic cortex	109	prognosis	neural network (NN) model	meningioma, glioma, and brain metastases	4 grades of glioma are present. Grades of meningioma and metastatic tumors were not specified	yes, with a different validation set	N/M	Dice Coefficient: ≤ 0.51 for all cases	the NN approach could predict individual motor activation using rs–fMRI data and could have promising clinical applications in brain tumor patients with anatomical and functional reorganizations.	One limitation of this study is that the NN method was only validated on adult brain tumor patients. It would be interesting to include pediatric data in future research. Also, a more advanced approach should be considered in future studies to increase the Dice coefficients (DC) of prediction.
3.	Context aware deep learning for brain tumor segmentation, subtype classification, and survival prediction using radiology images	335	prognosis	a Context–Aware deep neural network (CANet) architecture	Lower grade astrocytoma, IDH–mutant (A), oligodendroglioma, IDH–mutant, 1p/19q codeleted (O), and glioblastoma and diffuse astrocytic glioma with molecular features of glioblastoma, IDH–wildtype (G).	lower grade astrocytoma with IDH–mutant (Grade II or III), oligodendroglioma with IDH–mutant, 1p/19q codeleted (Grade II or III), and glioblastoma and diffuse astrocytic glioma with molecular features of globlastoma, IDH–wildtype (Grade IV).	Yes, data set was divided between training and validation set.	N/M	0.586	The results suggest that the proposed method offers robust tumor segmentation and survival prediction, respectively.	In future, we plan extensions to the proposed architecture by integrating whole slide image and molecular genetic features for tumor classification following new WHO criterion

4.	Topographic brain tumor anatomy drives seizure risk and enables machine learning based prediction	923	prognosis	generalized additive model (GAM)	GBM, Astrocytoma (diffuse or anaplastic), Oligoastrocytoma (diffuse or anaplastic), Oligodendroglioma (diffuse or anaplastic), Pilocytic astrocytoma, Medulloblastoma, Ependymoma, Developmental (DNET & ganglioglioma), Miscellaneous neuroepithelial, Primary CNS lymphoma, Metastases	WHO grade I, grade II, grade III, grade IV, and WHO grade NA	yes, the sample was divided into training set and internal validation set	0.79	0.72	This study identifies specific phylogenetic anatomical patterns as epileptic drivers. A generalized additive model (GAM) allowed the prediction of seizure risk using topographic, demographic and histopathologic data achieving fair performance while maintaining transparency.	A practical limitation of the presented model is the inherent difficulty of localizing brain tumors in such detail, requiring profound anatomical knowledge and training. A simplified version developed in the future will be required to establish a topographic anatomical model in clinical routine. Also, including molecular tumor markers might be of relevance to the seizure–risk prediction model.
5.	Predicting Inpatient Length of Stay After Brain Tumor Surgery: Developing Machine Learning Ensembles to Improve Predictive Performance	41 222	prognosis	Twenty–nine machine learning algorithms, including tree–based models, linear classifiers, support vector machines, RuleFit, neural networks, and naïve Bayes classifiers, were trained to predict the primary outcomes. The top performing algorithms were 2 gradient boosted trees and a Nystroem kernel support vector machine. These were combined with an elastic net to create an ensemble model.	N/M	N/M	yes, external validation from a different set.	N/M	0.555	An ML ensemble model predicts LOS with good performance on internal and external validation and yields clinical insights that may potentially improve patient outcomes. This systematic ML method can be applied to a broad range of clinical problems to improve patient care.	Future directions for this work include validating the ensemble on a larger external dataset, with more years represented, and validating the ensemble in a prospective fashion. It will also be important to build and validate an ensemble built from a single institution's data, allowing for tailoring of the ensemble to the specific practice milieu of the neurosurgeon(s) using the ensemble's predictions.

6.	Multi–Channel 3D Deep Feature Learning for Survival Time Prediction of Brain Tumor Patients Using Multi–Modal Neuroimages	68	prognosis	3D convolutional neural networks (CNNs)	High–grade glioma	WHO III: anaplastic astrocytomas, WHO III: anaplastic oligodendrogliomas, WHO IV: glioblastoma	Yes, Validation on Independent Dataset.	N/M	90.66%,	The experimental results demonstrate that this multi–model, multi–channel deep survival prediction framework achieves an accuracy of 90.66%, outperforming all the competing methods. This study indicates highly demanded effectiveness on prognosis of deep learning technique in neuro–oncological applications for better individualized treatment planning towards precision medicine.	In the future follow–up study, as more subjects with both genetic information and overall survival (OS) data, we will include genetic information for OS prediction. Also, for better generalizability of the proposed method, the participating subjects needs to be increased in the future. Moreover, In our future work, we will use all currently available features, including features from presurgical imaging, treatment ways, patient statuses before and after surgery, genetic information and molecular indicators (including IDH1, MGMT, 1p19q, TERT, and ATRX), to perform OS prediction.
7.	Predicting Survival in Patients with Brain Metastases Treated With Radiosurgery Using Artificial Neural Networks	196	prognosis	Artificial neural networks (ANNs)	Non–Small–Cell Lung Carcinoma, Renal Cell Carcinoma, Small–Cell Lung Carcinoma, Breast, Melanoma, Sarcoma	N/M	yes, the sample was divided into training, testing, and validation data sets	84%	N/M	ANNs outperform traditional statistical tools and scoring indexes for predicting individual patient prognosis. Their facile implementation, robustness in the presence of missing data, and ability to continuously learn make them excellent choices for use in complicated clinical environments.	Although it is probable that the results are generalizable to patients not undergoing radiosurgery, the study ought to be repeated in a larger, prospective cohort of general brain tumor patients to validate and hopefully improve on these results. Additionally, this study suffers from the drawbacks of all retrospective clinical studies and would benefit from validation in a prospective trial to mitigate bias.
8.	Multi–level dilated convolutional neural network for brain tumour segmentation and multi–view–based radiomics for overall survival prediction	335	prognosis	multi–level dilated CNN (MLDCNN) was used for the tumour segmentation. Multi–view (MV) and MS–based radiomic features was used for the overall survival prediction.	Glioma	Low grade glioma, High grad glioma (glioblastoma)	Yes, validation set from the same dataset of the training.	N/M	48.3%	It can be observed from the obtained results that the model performed better with low mean squared error (MSE) when Multi–view (MV) based features were used for training compared to single view–based features.	some pixels values were still missed out due to the dilation rate (skipping of pixels) between ker– nels to reduce the complexity of 3D CNN. By combining the kernels of multiple dilation rates, the skipping pixels overlap by the kernels with other dilation rates would reduce the number of skipping pixels.

9.	The Nomogram of MRI–based Radiomics with Complementary Visual Features by Machine Learning Improves Stratification of Glioblastoma Patients: A Multicenter Study	158	prognosis	five machine–learning methods were applied including logistic regression (LR) analysis, support vector machines (SVMs), as well as the Bayes and K nearest neighbor algorithms, and random forests to build the prediction model	Glioblastoma (GBM)	grade IV Glioblastoma	Yes, external validation set	N/M.	In the training set: 0.878; in the test set: 0.875	Radiomics nomogram integrated with radiomic signature, ependymal and pia mater involvement (EPI), and age was found to be robust for the stratification of Glioblastoma (GBM) patients into long– vs. short–term survival.	detailed medical history of and the treatment course for the GBM patients in this study were not available, such as Karnofsky Performance Scale score which is well established as one of the most important predictors, which might also influence their survival prediction result and should be considered in future studies. Also, future studies may benefit from the combined use of additional clinical data, variable treatments, anatomic information, and functional images.
10.	Analysis of machine learning algorithms in brain tumour prediction	3762	prognosis	machine learning algorithms such as Naïve Bayes, Support Vector Machine, Neural Networks, K nearest neighbor, Statistical Classifier (J48) and Ensemble Classifiers using voting technique.	Meningioma, Glioma and pituitary tumor	N/M	Yes, by 10–folds cross validation technique	Naïve Bayes: 0.989, Support vector Machine: 0.994, K nearest Neighbor: 0.992, Neural Network: 0.99, Decision Trees(j48): 0.987, Ensemble (Decision Tree+ SVM): 0.996	Naïve Bayes: 96.89, Support vector Machine: 97.61, K nearest Neighbor: 98.38, Neural Network: 98.80, Decision Trees(j48): 98.35, Ensemble (Decision Tree+ SVM): 98.9	Experimental results establish that Ensemble classifier technique gave the best accuracy to predict brain tumour.	Future work will include data augmentation and convolutional neural network model to classify the tumour which will additionally upgrade accuracy.
11.	Modeling of Textures to Predict Immune Cell Status and Survival of Brain Tumour Patients	151	prognosis	Gaussian mixture model (GMM) of learned 3D CNN features.	Glioma	Low grade glioma and glioblastoma multiforme (GBM)	Yes, using different validation set	N/M	Area under the curve value (accuracy) of (AUC) of 78.67%, 83.93% and 75.67% for Macrophage M1, Neutrophils and T Cells Follicular Helper, respectively.	Our findings indicate that the proposed features (DRFs) used in random forest (RF) models may significantly consider prognosticating patients with brain tumour prior to surgery through regularly acquired imaging data.	There is a plan to extend the suggested deep radiomic pipeline through different types of cancer.

12.	Combining multimodal imaging and treatment features improves machine learning-based prognostic assessment in patients with glioblastoma multiforme	189	prognosis	the random forest algorithm and random survival forest (RSF) models	Glioblastoma (GBM)	Grade IV	Yes, by internal validation	N/M	the highest prognostic performance was achieved by adding treatment information with combination of all features reaching up to C-indices of 0.73 (0.62-0.84) and 0.71 (0.60-0.81) on the validation set for OS and PFS, respectively.	MRI-based features were the most relevant feature class for prognostic assessment. Combining clinical, pathological, and imaging information increased predictive power for overall survival (OS) and progression-free survival (PFS). A further increase was achieved by adding treat– ment features.	In the future, prognostic performance might be enhanced by including texture features or dynamic FET-PET/ CT measures.
13.	Radiomic features from the peritumoral brain parenchyma on treatment–naïve multi–parametric MR imaging predict long versus short–term survival in glioblastoma multiforme: Preliminary findings	65	prognosis	random forest (RF) classifier	Glioblastoma Multiforme	Grade 4	Three–fold cross validation	N/M but the Concordance indices which reflect accuracy = 0.735	N/M	The radiomic features from the peritumoral zones appear to be predictive of overall patient survival. Peritumoral radiomics along with clinical factors are highly predictive of Glioblastoma outcome. Identifying prognostic markers can assist in making personalized therapy decisions in Glioblastoma.	The addition of complementary imaging parameters in may further improve survival prediction using radiomic analysis. Additionally, add larger GBM cohort with inclusion of intermediate survival patients as well as independent validation of the radiomic features identified in this preliminary analysis, while taking into account the extent of resection and subsequent treatment.
14.	Radiomics in peritumoral non–enhancing regions: fractional anisotropy and cerebral blood volume improve prediction of local progression and overall survival in patients with glioblastoma.	83	Prognosis	least absolute shrinkage and selection operator (LASSO)	Glioblastoma	N/M	10–fold cross validation	N/M	N/M	The radiomics approach reflects tissue heterogeneity better than single imaging parameters by comparing the diagnostic performance using FA and CBV. The prognostic performance of the combined radiomics approach was superior to that of the single radiomics model and single parameter approaches	the radiomics model should be independently and prospectively verified, preferably in a multicenter setting.

Table 1: The articles discussing AI in neuro–oncology prognosis.

N/M Not mentioned

No	Study title	Sample size	AI use	Modality used	Tumor type	Tumor grading	Validation method	Precision	Accuracy	Recommendation	Future direction
1.	Facilitating MR–Guided Adaptive Proton Therapy in Children Using Deep Learning–Based Synthetic CT	125	treatment	self–attention cycle–generative adversarial networks (cycle–GANs)	Not mentioned. Only brain tumors.	N/M	No	N/M	N/M	The novel cycle–GAN model with self–attention outperforms conventional cycle–GAN for children with brain tumors. Encouraging dosimetric results suggest that sCT generation can be used to identify patients who would benefit from adaptive replanning.	Given that any model could potentially underperform under certain circumstances, future work should focus on developing a metric to predict proton therapy dose accuracy of an sCT when a ''gold standard'' comparison is not available.
2.	A pilot study of machine–learning based automated planning for primary brain tumors	95	treatment	Atlas regression forests (ARFs) and conditional random field (CRF) model	Glioma, meningioma, ependymoma, medulloblastoma, craniopharyngioma, others	N/M	No	N/M	N/M	Use of an automated ML method to aid RT planning for children and young adults with primary brain tumors is dosimetrically feasible and can be successfully used to create high-quality 54 Gy RT plans.	Different training sets and models are likely needed for use with two–phase plans or other prescriptions because of differing dose–constraints on organs-at-risk (OARs). Clinical implementation to ensure continued feasibility is required.
3.	Deep–learning–based synthesis of post–contrast T1–weighted MRI for tumor response assessment in neuro–oncology: a multicenter, retrospective cohort study	1585	treatment	deep convolutional neural networks (dCNN)	glioblastoma	N/M	Yes, a validation set from the sample	N/M	N/M	Generating synthetic post–contrast T1–weighted MRI from pre–contrast MRI using dCNN is feasible and quantification of the contrast–enhancing tumor burden from synthetic post–contrast T1–weighted MRI allows assessment of the patient's response to treatment with no significant difference by comparison with true post–contrast T1–weighted sequences with administration of Gadolinium–based contrast agents (GBCAs).	Future large–scale studies could improve the performance of the dCNNs for generating synthetic post–contrast T1–weighted images without compromising generalizability. Also, although the clinical use of synthetic post–contrast T1–weighted MRI was shown for tumor response assessment in the EORTC–26101 test set, discrepancies in the time to progression on a per case basis need to be addressed in future studies. Adding to that, fully convolutional networks are a suitable replacement for the U–Net and should be considered in the future. Moreover, aA comparison of synthetic post–contrast T1–weighted MRI based on pre– contrast MRI sequences with those based on low–dose contrast media applications needs to be addressed in future studies and an investigation of real–time practicability and validity of the proposed methodology.

4.	Machine learning assisted intraoperative assessment of brain tumor margins using HRMAS NMR spectroscopy	565	treatment	Multiple ML algorithms including partial least squares discriminant analysis (PLS–DA), Random Forest (RF) classifier, support vector machine classifier (SVM), and Convolutional neural networks (CNN)	astrocytoma, glioblastoma, oligodendroglioma, oligoastrocytoma, ganglioglioma, dysembryoplastic neuroepithelial tumors, gliosarcoma	Pilocytic astrocytoma (AST–I), astrocytoma grade II, astrocytoma grade III, glioblastoma, oligodendroglioma grade II, oligodendroglioma grade II–III, oligodendroglioma grade III, oligoastrocytoma grade II, oligoastrocytoma grade III, oligoastrocytoma grade II–III, ganglioglioma grade II, ganglioglioma grade III, dysembryoplastic neuroepithelial tumors, gliosarcoma	Yes, 8–fold cross validation approach	93.4%	85.6%	Our results show that machine learning based approach can distinguish samples with and without tumor cells accurately and effectively. Furthermore, we validate that previously identified biological indicators of tumors play an important role for this classification. The algorithm also suggests new and uncharacterized tumor indicators.	Further research and validation is needed to establish an understanding of the compounds in those regions and their relation to tumor metabolism. Also, these regions harbor shared groups of several metabolites and further work is needed to validate their ties to glioma metabolism and their status as a glioma biomarker.
5.	Intelligent SERS Navigation System Guiding Brain Tumor Surgery by Intraoperatively Delineating the Metabolic Acidosis	5 animal models with glioblastoma allografts (rats) and 5 human patients	treatment	surface–enhanced Raman scattering (SERS) navigation system	Glioma	N/M	No	N/M	N/M	The overall survival of animal models post the SERS system guided surgery is significantly increased in comparison to the conventional strategy used in clinical practice. This SERS system holds the promise in accelerating clinical transition of acidic margin–guided surgery for solid tumors with infiltrative nature.	N/M
6.	Predicting the local response of metastatic brain tumor to gamma knife radiosurgery by radiomics with a machine learning method.	157	treatment	neural network classifier with 10 hidden layers	Brain tumor metastatic lesions	N/M	five–fold cross–validation	N/M	78	The NN model using the radiomics features is more accurate than the visual evaluation method in predicting the local response of brain metastases to GKRS.	utilizing images taken by other imaging modalities. adding radiomics features of other MR imaging protocols, dosimetric parameters such as prescribed dose and standard biomarkers.
7.	The radiomic–clinical model using the SHAP method for assessing the treatment response of whole–brain radiotherapy: a multicentric study.	228	treatment	LASSO for feature selection, Support vector machine for model creation	Brain tumor metastatic lesions	N/M	Internal validation 44 patients for validation	N/M	92.8%	the use of SHAP force plot showed feature's value affected the feature's impact. Finally, the radiomic–clinical model with the SHAP method is useful for personalized WBRT in an explainable way.	Use multiparameter–MRI–based radiomics that contain other biophysical properties. Use histopathologic marker expression to assess response.

Table 2: The articles discussing AI in neuro–oncology treatment.

N/M Not mentioned

them to predict the LOS. Then, they ranked them and grouped the top algorithms in one ensemble to create a more effective prediction ensemble, which allowed them to utilize the strengths of all high–ranked algorithms. Their model eventually outperformed LOS prediction for internal and external validation. In another analysis of a group of six ML algorithms to predict a brain tumor in an early stage, the ensemble classifier technique was found to be the most accurate one [6].

Predict the tumor growth:

A study interested in **tumor growth prediction** suggested combining mathematical and ML models [7]. The main objectives were to enhance these individualized predictions even with limited data regarding the disease course or mechanism where other prediction models fail. Using a novel method called BaM3, based on a combination of ML and mathematics in the Bayesian framework. According to this study's results, the prediction improved in more than 95% of the patients.

Kim and colleagues studied peritumoral non–enhancing region to predict recurrence of glioblastoma. The LASSO penalization method used contrast–enhanced T1–weighted and fluid–attenuated inversion recovery images to extract radiomic features, specifically from fractional anisotropy (FA) and normalized cerebral blood volume (CBV) maps [32]. It predicts six months tumor progression with a sensitivity of 94.1% and 57.1% specificity [32]

Predict the survival:

Survival prediction is an integral part of neuro–oncology prognosis. A study published in 2013 about the use of Artificial neural networks (ANN) to predict the 1–year survival of patients after stereotactic radiosurgery[8]. They also compared a single ANN, an ensemble of 5 ANN, a logistic regression, and existing traditional predictive tools for 1–year survival prognosis. They found that the ensemble of 5 ANN outperformed all the other prediction tools they compared and was able to predict better the 1–year survival of their patients. A more recent study looked at the overall survival prediction of patients with high–grade glioma [9]. They proposed a more advanced technique using multimodal and multi–channel 3D deep feature learning, which they claim outperformed all the previous competing methods (accuracy of 90.66%). In the following year, another published article used a similar model to predict the overall survival of brain tumor patients [10]. Another recent research on glioblastoma overall survival used a modified deep 3D multi–level dilated convolutional neural network (CNN) for tumor segmentation and survival prediction [11].

On the other hand, Chaddad and colleagues reported a statistical significance for using deep radiomics features or specific immune cell markers to predict the survival of brain tumor patients. Gaussian mixture model (GMM) of learned 3D CNN features has been used [12]. Another study suggested combining radiomics features with certain visual features to better classify glioblastoma patients into extended and short–survival groups [1].

Peeken and colleagues comprehensively used clinical, pathological, semantic MRI-based, and FET-PET/CT-derived information to train ML models for prediction of patients' overall survival (OS) and progression-free survival (PFS) [30]. It is found that MRI-based model showed the highest performance in prediction of OS and PFS. While when combining the information from all sources, the performance in prediction is higher than all individual sources.

Prasanna and colleagues used RF classifier to extract radiomic features from peritumoral zone to predict glioblastoma patient survival [31]. It is used in combination with the other clinical features to predict short (less than 7 months) and long–term (greater than 18 months) survival.

Predict the seizure risk with a brain tumor:

Interestingly, ML use in neuro–oncology prognosis is not only limited to the course of the tumor but also to predict other related aspects. For example, Akeret and colleagues investigated using a generalized additive method (GAM) to **predict the seizure risk with a brain tumor** [14]. With the GAM they developed, seizure risk prediction was better when combining topographic, histopathologic, and demographic data. While Niu and colleagues studied the prediction of motor area activation before brain surgery using the neural network method by analyzing presurgical functional MRI images [15].

With the noticed rise in published prediction models in oncology, a systematic review was done to assess the methodological conduct of studies using AI in multiple tumors prognoses [3]. Sixty–two publications were included, and more than 150 prediction models were classified and evaluated. It has been found that prediction models lack integral elements in their development and methodology. There is a need for direction of more focus and awareness toward basic prediction modeling standards such as sample size estimation and validation.

Treatment

Brain tumor treatment is a multi–step process that usually starts by detection and imaging, until follow–up. In almost every step, AI is integrated to enhance overall management outcomes [16]. Those AI models that are directly associated with the treatment will be listed

below. Generally, there is a scarcity of articles specifically discussing AI application in brain tumor treatment, instead many are discussing multiple entities of body tumors including brain tumors. There is inconsistency in reporting the model performance, certain articles mention the accuracy while others report the precision. The highest reported accuracy is 85.6%, and precision is 93.4% in the same study [19].

Predict response to gamma knife radiosurgery:

Kawahara and colleagues used ML to predict brain tumor metastasis response to gamma knife radiosurgery[13]. The proposed model extracts radiomic features from MRI images and analyzes them. From the MRI images, 740 features were extracted, then reduced into seven features which is the least number efficient enough for prediction. The data from these seven features were used to construct the prediction model by a neural network classifier. The proposed method was more accurate than the usual visual evaluation method with an accuracy of (78%) compared to (44%) by the usual visual evaluation. This made the proposed approach more useful to the physician in getting an accurate prediction of the treatment outcome than the traditional method [13].

For the assessment of the treatment response of brain tumor to whole–brain radiotherapy (WBRT), Y. Wang and colleagues used ML support vector machine (SVM) on pretreatment MRIs. Later used SHapley Additive exPlanations (SHAP) to explain ML model output by prioritizing the importance of features. The model accuracy is 92.8% in the testing set, and the use of SHAP force plot showed feature's value affected the feature's impact. Finally, the radiomic–clinical model with the SHAP method is useful for personalized WBRT in an explainable way [33].

Facilitate precise radiotherapy treatment:

Pediatrics with brain tumors receive MR–Guided adaptive proton therapy which requires a repeat of CTs. Therefore, a synthetic CT has been proposed to limit the excess (unneeded) exposure to radiation and anesthesia using a novel deep learning method known as self–attention cycle–generative adversarial networks (cycle–GANs) which is suggested by Wang and colleagues to produce more accurate synthetic CTs. Their results showed that this novel type of cycle–GANs outperforms the conventional cycle–GANs in generation of synthetic CT for pediatric brain tumors [17].

A pilot study published in 2022 revealed the possibility of integrating ML methods to plan **radiotherapy doses** for primary brain tumors in **pediatrics** and young adults. The model links the image features and predicted doses to develop the plan [18]. The proposed model successfully created deliverable high–quality 54 Gy radiotherapy plans in all patients in the testing set, however further evaluation after clinical implementation is required.

Determine tumor margins for treatment:

Resecting brain tumors such as glioma requires accurate assessment intraoperatively to ensure no leftovers are behind and **decrease the chance of recurren**ce. A targeted method was developed using High–Resolution Magic Angle Spinning Nuclear Magnetic Resonance (HRMAS NMR) to **identify tumor margins** using known biomarker metabolites. In order to expand the use of this method to have an untargeted assessment, including the unknown metabolites as well, additionally, it is suggested to build a novel ML technique [19].

Another recent study proposed using an intelligent surface–enhanced Raman scattering (SERS) navigation system **to determine glioma margins**. This is done by measuring the pH without needing an exogenous probe, as cancer margins are considered more acidic [20].

Differentiate treatment adverse effects from metastases:

The differentiation of local brain tumor metastasis from radiation injury is challenging with conventional MRI. Radiomics feature analysis was found to be useful for differentiation [16]. Multiple studies suggested different methods to overcome this challenge. Peng and colleagues group developed an AI model with the IsoSVM algorithm that used brain radiomics [21]. It used fifty–one extracted radiomics features from suspicious FLAIR MRI images. This developed model outperformed experienced radiologists and achieved an AUC of 0.81. Zhang and colleagues evaluated MRI images from two different time points after gamma knife radiosurgery [22]. By this, they could monitor tumor progression and compare it to radiation necrosis using the changes in radiomics features and achieved an AUC of 0.73.

Differentiate treatment adverse effects from relapse:

On the other hand, other research groups investigated the use of amino acid PET to **differentiate between local relapse and radiation injury**. It has been found that time–activity curves (TAC) are a helpful factor for differentiation [23]. However, O–(2–[18F]fluoroethyl)–L–tyrosine positron–emission tomography (FET PET) scan is time–consuming [23][16]. Thus, combining conventional FET PET with textural features resulted in a diagnostic accuracy reaching 85% [24]. A more recent study compared

MRI or FET PET alone and in combination. It was noticed that a combination of FET PET/MRI resulted in a diagnostic accuracy reaching 89% [25].

Bhandari and colleagues published a meta–analysis focusing on exploring the effect of ML in the differentiation between treatment–related effects and true tumor progression in brain tumors [26]. This systematic review revealed that ML can distinguish between treatment–related effects and true tumor progression in brain tumors with good performance using ML–based imaging models. However, it is found that there are some issues with the existing evidence related to the study quality, standardization, sample size, or external validation. Eventually, this will impact the generalizability of the data and the clinical application [16] [26]. Therefore, the standardization in results reporting of similar studies is advised.

Challenges of AI in neuro–oncology:

With that promising advance in AI application in the medical field, still challenges exist, which require attention and solutions. These challenges range from small data that is required for training to ethical restrictions in building and deployment of such technologies. The requirement of robust updated policies regarding its application in healthcare systems is another challenge.

Ethical challenges:

Every advance in any field has its own challenges and obstacles and one major challenge in using AI in the medical field is its ethical dilemma.

It arises from the fact that algorithms reflect human biases. This is evidenced by incidents from other fields that applied AI algorithms. These biases will appear in the form of giving similar patients different treatment plans leading to a suboptimal approach and potential harm. This is a clear violation of the Hippocratic oath: ("First, do no harm").

Doctors and patients around the world are doubting these machines and algorithms in decision–making. One study showed that over 63% of adults in the United Kingdom felt uncomfortable with AI replacing the conventional decision–making process [27].

With the incredible growth of AI applications in the medical field, there is a critical need for ethical guidelines that allow optimal use of these new technologies. Also, to prevent converting this technology into a black box as the data sets, they are built on are unknown which will lead to doubtful outcomes.

The black box effect arises because of unclear interpretable parameters. The same reason makes it difficult for organizations like the Food and Drug Association FDA to ensure consistency of performance.

Generalizability and lack of external validation:

Although the highly accurate results from AI applications in detecting millimeter–sized brain metastasis, there is a challenge when applying those algorithms to different unseen data. Most AI studies are trained and tested with data from a single institution and are deficient in external validation. For that, it's important to have strict external validation with different populations to confirm the highest accuracy and steadiness of AI algorithm performance [28].

Data size:

Large data sets are used to train AI algorithms, in the commercial use of AI the dataset is larger than those used to train AI in the medical field. This could be attributed to a lack of collaboration and sharing of patient data due to privacy concerns regarding patient data protection. To overcome this challenge, sharing data and having a centralized open–access repository are recommended[27].

Future directions:

The advance in AI research in neuro–oncology is growing and will continue to increase in the next few years despite the challenges. Many countries invest generously in developing AI research centers to create accurate and powerful AI systems. Furthermore, agencies working to develop concise and clear regulations regarding AI applications on patient care and data safety [28]. **Figure 5 demonstrates the future directions of AI in neuro–oncology.** To complement knowledge gaps, neuro–oncologist needs to increase interaction with AI engineers as multidisciplinary collaboration is the key to success.

Conclusion:

AI integration in the medical field is important to overcome the current challenges and provide personalized care for patients. Implementation of such new technology in biomedical problem–solving, especially neuro–oncology is promising. The use of artificial neural networks to analyze data and recognize patterns for brain tumor behavior prediction is a huge revolution in neuro–oncology. The development of an accurate AI model for survival prediction requires huge data sets to feed the developed ML algorithm in order to get generalizable data. The potential application of AI technologies in neuro–oncology prognosis is incredible; however, it faces many challenges regarding accuracy and the cost of development of such systems. In brain tumor treatment AI plays a pivotal role in advancing precision medicine techniques. AI aids in the treatment of brain tumor patients starting from identification of

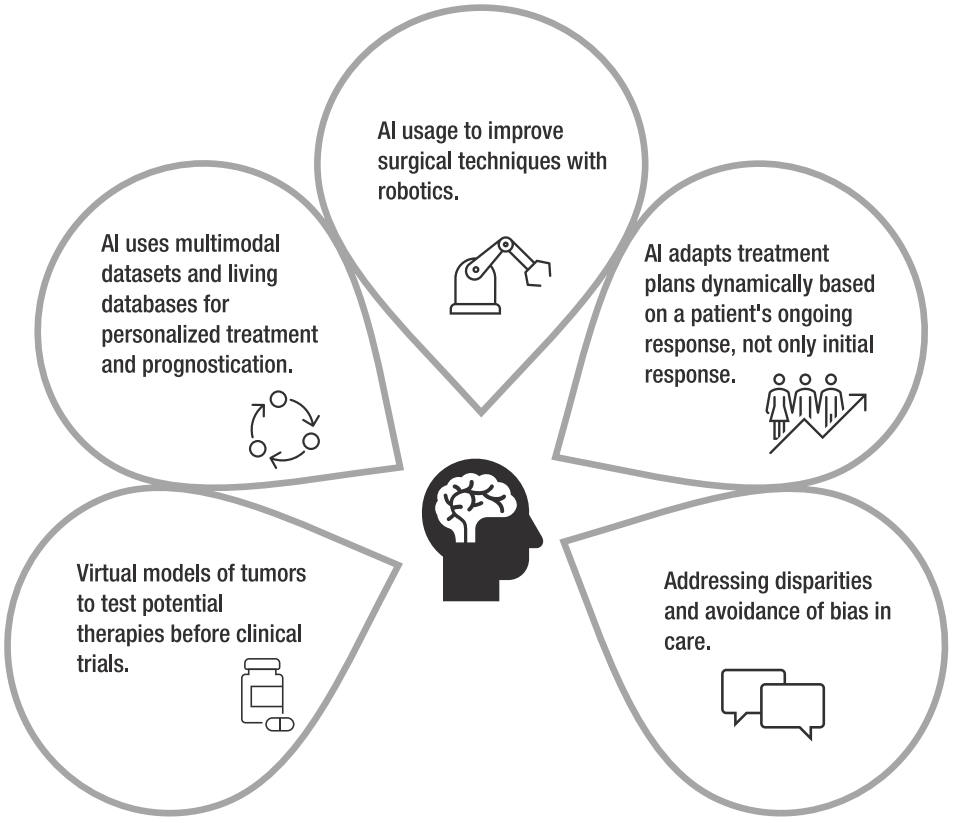


Figure 5: Future directions of AI in neuro–oncology.

the tumor, segmentation, grading, assisting in choosing the best treatment modality, and monitoring of tumor recurrence. Furthermore, it forecasts the development of new medications and the best dose choices. Careful application of these technologies is important since it deals with patients' lives.

Acknowledgements

Not applicable

Funding

No funding was received

Availability of data and materials

Not applicable

Authors' contributions

Adham Al–Rahbi, Tariq Al–Habsi, and Tariq Al–Saadi: Planning, conceptualization & design. **Adham Al–Rahbi:** Involved in articles collection. **Adham Al–Rahbi:** Involved in preparation of the figures and the tables. **Adham Al–Rahbi, Tariq Al–Habsi:** Writing the first draft of the manuscript. **Adham Al–Rahbi:** Editing the final manuscript. **Tariq Al–Saadi:** Revising the work critically for important intellectual content and final approval of the version to be published. **Adham Al–Rahbi, Tariq Al–Habsi, and Tariq Al–Saadi** have read and agreed to the published version of the manuscript.

Ethics approval and consent to participate

Not applicable

Patient consent for publication

Not applicable

Competing interests

The authors declare that they have no competing interests.

References:

1. Xu, Y., He, X., Li, Y., Pang, P., Shu, Z., & Gong, X. (2021). The Nomogram of MRI-based Radiomics with Complementary Visual Features by Machine Learning Improves Stratification of Glioblastoma Patients: A Multicenter Study. *Journal of Magnetic Resonance Imaging*, *54*(2), 571–583. https://doi.org/10.1002/jmri.27536

2. Fan, Y., Zhang, X., Gao, C., Jiang, S., Wu, H., Liu, Z., & Dou, T. (2022). Burden and trends of brain and central nervous system cancer from 1990 to 2019 at the global, regional, and country levels. *Archives of Public Health*, *80*(1). https://doi.org/10.1186/s13690–022–00965–5

3. Dhiman, P., Ma, J., Navarro, C. L. A., Speich, B., Bullock, G., Damen, J. a. A., Hooft, L., Kirtley, S., Riley, R. D., Van Calster, B., Moons, K. G. M., & Collins, G. S. (2022). Methodological conduct of prognostic prediction models developed using machine learning in oncology: a systematic review. *BMC Medical Research Methodology*, *22*(1). https://doi.org/10.1186/s12874–022–01577–x

4. Muhlestein, W. E., Akagi, D. S., Davies, J. M., & Chambless, L. B. (2018). Predicting inpatient length of stay after brain tumor surgery: Developing machine learning ensembles to improve predictive performance. *Neurosurgery*, *85*(3), 384–393. https://doi.org/10.1093/neuros/nyy343

5. Preetha, C. J., Meredig, H., Brugnara, G., Mahmutoglu, M. A., Foltyn, M., Isensee, F., Kessler, T., Pflüger, I., Schell, M., Neuberger, U., Petersen, J., Wick, A., Heiland, S., Debus, J., Platten, M., Idbaih, A., Brandes, A. A., Winkler, F., Van Den Bent, M. J., . . . Vollmuth, P. (2021). Deep–learning–based synthesis of post–contrast T1–weighted MRI for tumour response assessment in neuro–oncology: a multicentre, retrospective cohort study. *The Lancet Digital Health*, *3*(12), e784–e794. https://doi.org/10.1016/s2589–7500(21)00205–3

6. Gupta, M., Sharma, S. K., Saxena, R., & Arora, S. (2021). Analysis of machine learning algorithms in brain tumour prediction. Journal of Physics Conference Series, 2070(1), 012090. https://doi.org/10.1088/1742–6596/2070/1/012090

7. Mascheroni, P., Savvopoulos, S., Alfonso, J. C. L., Meyer–Hermann, M., & Hatzikirou, H. (2021). Improving personalized tumor growth predictions using a Bayesian combination of mechanistic modeling and machine learning. *Communications Medicine*, *1*(1). https://doi.org/10.1038/s43856–021–00020–4

8. Oermann, E. K., Kress, M. S., Collins, B. T., Collins, S. P., Morris, D., Ahalt, S. C., & Ewend, M. G. (2013). Predicting survival in patients with brain metastases treated with radiosurgery using artificial neural networks. *Neurosurgery*, *72*(6), 944–952. https://doi.org/10.1227/neu.0b013e31828ea04b

9. Nie, D., Lu, J., Zhang, H., Adeli, E., Wang, J., Yu, Z., Liu, L., Wang, Q., Wu, J., & Shen, D. (2019). Multi–Channel 3D deep feature learning for survival time prediction of brain tumor patients using Multi–Modal Neuroimages. *Scientific Reports*, *9*(1). https://doi.org/10.1038/s41598–018–37387–9

10. Pei, L., Vidyaratne, L., Rahman, M. M., & Iftekharuddin, K. M. (2020). Context aware deep learning for brain tumor segmentation, subtype classification, and survival prediction using radiology images. *Scientific Reports*, *10*(1). https://doi.org/10.1038/s41598–020–74419–9

11. Rafi, A., Madni, T. M., Janjua, U. I., Ali, M. J., & Abid, M. N. (2021). Multi-level dilated convolutional neural network for brain tumour segmentation and multi-view-based radiomics for overall survival prediction. *International Journal of Imaging Systems and Technology*, *31*(3), 1519–1535. https://doi.org/10.1002/ima.22549

12. Chaddad, A., Zhang, M., Hassan, L., & Niazi, T. (2021). Modeling of textures to predict immune cell status and survival of brain tumour patients. *2022 IEEE 19th International Symposium on Biomedical Imaging (ISBI)*, 1067–1071. https://doi.org/10.1109/isbi48211.2021.9434053

13. Kawahara, D., Tang, X., Lee, C. K., Nagata, Y., & Watanabe, Y. (2021). Predicting the local response of metastatic brain tumor to gamma knife radiosurgery by radiomics with a machine learning method. *Frontiers in Oncology*, *10*. https://doi.org/10.3389/fonc.2020.569461

14. Akeret, K., Stumpo, V., Staartjes, V. E., Vasella, F., Velz, J., Marinoni, F., Dufour, J., Imbach, L. L., Regli, L., Serra, C., & Krayenbühl, N. (2020). Topographic brain tumor anatomy drives seizure risk and enables machine learning based prediction. *NeuroImage Clinical*, *28*, 102506. https://doi.org/10.1016/j.nicl.2020.102506

15. Niu, C., Wang, Y., Cohen, A. D., Liu, X., Li, H., Lin, P., Chen, Z., Min, Z., Li, W., Ling, X., Wen, X., Wang, M., Thompson, H. P., & Zhang, M. (2021). Machine learning may predict individual hand motor activation from resting–state fMRI in patients with brain tumors in perirolandic cortex. *European Radiology*, *31*(7), 5253–5262. https://doi.org/10.1007/s00330–021–07825–w

16. Kocher, M., Ruge, M. I., Galldiks, N., & Lohmann, P. (2020). Applications of radiomics and machine learning for radiotherapy of malignant brain tumors. *Strahlentherapie Und Onkologie*, *196*(10), 856–867. https://doi.org/10.1007/s00066–020–01626–8

17. Wang, C., Uh, J., Merchant, T. E., Hua, C., & Acharya, S. (2021). Facilitating MR–Guided adaptive proton therapy in children using Deep Learning–Based synthetic CT. *International Journal of Particle Therapy*, *8*(3), 11–20. https://doi.org/10.14338/ijpt–20–00099.1

18. Tsang, D. S., Tsui, G., McIntosh, C., Purdie, T., Bauman, G., Dama, H., Laperriere, N., Millar, B., Shultz, D. B., Ahmed, S., Khandwala, M., & Hodgson, D. C. (2022). A pilot study of machine–learning based automated planning for primary brain tumours. *Radiation Oncology*, *17*(1). https://doi.org/10.1186/s13014–021–01967–3

19. Cakmakci, D., Karakaslar, E. O., Ruhland, E., Chenard, M., Proust, F., Piotto, M., Namer, I. J., & Cicek, A. E. (2020). Machine learning assisted intraoperative assessment of brain tumor margins using HRMAS NMR spectroscopy. *PLoS Computational Biology*, *16*(11), e1008184. https://doi.org/10.1371/journal.pcbi.1008184

20. Jin, Z., Yue, Q., Duan, W., Sui, A., Zhao, B., Deng, Y., Zhai, Y., Zhang, Y., Sun, T., Zhang, G., Han, L., Mao, Y., Yu, J., Zhang, X., & Li, C. (2022). Intelligent SERS navigation system guiding brain tumor surgery by intraoperatively delineating the metabolic acidosis. *Advanced Science*, *9*(7). https://doi.org/10.1002/advs.202104935

21. Peng, L., Parekh, V., Huang, P., Lin, D. D., Sheikh, K., Baker, B., Kirschbaum, T., Silvestri, F., Son, J., Robinson, A., Huang, E., Ames, H., Grimm, J., Chen, L., Shen, C., Soike, M., McTyre, E., Redmond, K., Lim, M., . . . Kleinberg, L. (2018). Distinguishing true progression from radionecrosis after stereotactic radiation therapy for brain metastases with machine learning and radiomics. *International Journal of Radiation Oncology*Biology*Physics*, *102*(4), 1236–1243. https://doi.org/10.1016/j.ijrobp.2018.05.041

22. Zhang, Z., Yang, J., Ho, A., Jiang, W., Logan, J., Wang, X., Brown, P. D., McGovern, S. L., Guha–Thakurta, N., Ferguson, S. D., Fave, X., Zhang, L., Mackin, D., Court, L. E., & Li, J. (2017). A predictive model for distinguishing radiation necrosis from tumour progression after gamma knife radiosurgery based on radiomic features from MR images. *European Radiology*, *28*(6), 2255–2263. https://doi.org/10.1007/s00330–017–5154–8

23. Ceccon, G., Lohmann, P., Stoffels, G., Judov, N., Filss, C. P., Rapp, M., Bauer, E., Hamisch, C., Ruge, M. I., Kocher, M., Kuchelmeister, K., Sellhaus, B., Sabel, M., Fink, G. R., Shah, N. J., Langen, K., & Galldiks, N. (2016). DynamicO–(2–18F–fluoroethyl)–L–tyrosine positron emission tomography differentiates brain metastasis recurrence from radiation injury after radiotherapy. *Neuro–Oncology*, now149. https://doi.org/10.1093/neuonc/now149

24. Lohmann, P., Stoffels, G., Ceccon, G., Rapp, M., Sabel, M., Filss, C. P., Kamp, M. A., Stegmayr, C., Neumaier, B., Shah, N. J., Langen, K., & Galldiks, N. (2016). Radiation injury vs. recurrent brain metastasis: combining textural feature radiomics analysis and standard parameters may increase 18F–FET PET accuracy without dynamic scans. *European Radiology*, *27*(7), 2916–2927. https://doi.org/10.1007/s00330–016–4638–2

25. Lohmann, P., Kocher, M., Ceccon, G., Bauer, E. K., Stoffels, G., Viswanathan, S., Ruge, M. I., Neumaier, B., Shah, N. J., Fink, G. R., Langen, K., & Galldiks, N. (2018). Combined FET PET/MRI radiomics differentiates radiation injury from recurrent brain metastasis. *NeuroImage Clinical*, *20*, 537–542. https://doi.org/10.1016/j.nicl.2018.08.024

26. Bhandari, A., Marwah, R., Smith, J., Nguyen, D., Bhatti, A., Lim, C. P., & Lasocki, A. (2022). Machine learning imaging applications in the differentiation of true tumour progression from treatment-related effects in brain tumours: A systematic review and meta-analysis. *Journal of Medical Imaging and Radiation Oncology*, *66*(6), 781–797. https://doi.org/10.1111/1754–9485.13436

27. Fenech M, Strukelj N, Buston O, Future Advocacy. ETHICAL, SOCIAL, AND POLITICAL CHALLENGES OF ARTIFICIAL INTELLIGENCE IN HEALTH [Internet]. Future Advocacy. 2018. Available from: https://wellcome.org/sites/default/files/ai–in–health–ethical–social–political–challenges.pdf

28. Xu, J., Meng, Y., Qiu, K., Topatana, W., Li, S., Wei, C., Chen, T., Chen, M., Ding, Z., & Niu, G. (2022). Applications of Artificial intelligence based on medical imaging in Glioma: current state and future challenges. *Frontiers in Oncology*, *12*. https://doi.org/10.3389/fonc.2022.892056

29. Al–Rahbi, A., & Al–Saadi, T. (2025). Leveraging artificial intelligence for brain tumor classification. In *Science and Technology: Developments and Applications* (Vol. 5, pp. 29–79). https://doi.org/10.9734/bpi/stda/v5/1964

30. Peeken, J. C., Goldberg, T., Pyka, T., Bernhofer, M., Wiestler, B., Kessel, K. A., Tafti, P. D., Nüsslin, F., Braun, A. E., Zimmer, C., Rost, B., & Combs, S. E. (2018). Combining multimodal imaging and treatment features improves machine learning–based prognostic assessment in patients with glioblastoma multiforme. *Cancer Medicine*, *8*(1), 128–136. https://doi.org/10.1002/cam4.1908

31. Prasanna, P., Patel, J., Partovi, S., Madabhushi, A., & Tiwari, P. (2016). Radiomic features from the peritumoral brain parenchyma on treatment–naïve multi–parametric MR imaging predict long versus short–term survival in glioblastoma multiforme: Preliminary findings. *European Radiology*, *27*(10), 4188–4197. https://doi.org/10.1007/s00330–016–4637–3

32. Kim, J. Y., Yoon, M. J., Park, J. E., Choi, E. J., Lee, J., & Kim, H. S. (2019). Radiomics in peritumoral non–enhancing regions: fractional anisotropy and cerebral blood volume improve prediction of local progression and overall survival in patients with glioblastoma. *Neuroradiology*, *61*(11), 1261–1272. https://doi.org/10.1007/s00234–019–02255–4

33. Wang, Y., Lang, J., Zuo, J. Z., Dong, Y., Hu, Z., Xu, X., Zhang, Y., Wang, Q., Yang, L., Wong, S. T. C., Wang, H., & Li, H. (2022). The radiomic–clinical model using the SHAP method for assessing the treatment response of whole–brain radiotherapy: a multicentric study. *European Radiology*, *32*(12), 8737–8747. https://doi.org/10.1007/s00330–022–08887–0

KFAS
مؤسسة الكويت للتقدم العلمي
Kuwait Foundation for the Advancement of Sciences

The Gulf Journal of Oncology is published with the financial support from the Kuwait Foundation for the Advancement of Sciences





Contact :
The Gulf Federation for Cancer Control
P. O. Box 26733 Safat 13128 Kuwait
Tel. (00965) 22530186 / 22530184 Fax: (00965) 22510137
website : http://www.gffcc.org
email : gffccku@yahoo.com

Electronic Edition
www.gffcc.org/journal