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Mapping the intellectual landscape: A comprehensive scientometric review of AI-driven brain tumor analysis from MRI (2021-2025)

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A B S T R A C T

The publication under consideration provides a detailed scientometric analysis of two hundred scientific publications, which were obtained from the Scopus database, and the main focus was the intersection of Magnetic Resonance Imaging (MRI), brain tumor research, and artificial intelligence (AI), or at least data science. The analytical process sharply defined the intellectual structure and development of the field from 2021 to 2025. Among the important observations was the predomination of the research interests directed at the deep learning models for segmentation and classification, the growing importance of Explainable AI (XAI) to mediate between the model's performance and clinical acceptance, and the flourishing of radiomics for oncological prediction. The geographical distribution of the field indicates that it is a world-wide activity with the major input coming from China, India, America, Germany, and Pakistan. The authors and institutions whose works have had the greatest impact are revealed, and they are frequently found being associated with the topics of taking the client in combination with data coming from different modalities through the process of data fusion and the clinical translation of technologies. This literature review maps out these trends in order to counsel the researchers who are just starting and in the meantime to indicate the directions of the future research, such as the need for solid and consistent; federated learning and creating lightweight models that are suitable for clinical deployment.

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1. Introduction

Brain tumors are undoubtedly one of the greatest difficulties of modern medicine, and their very complex pathology, location in critical areas, and frequently bleak prognosis to high-grade gliomas like glioblastoma multi-form do not help. The World Health Organization (WHO) classification of tumors in the central nervous system has made great strides over the last few years, as it now includes molecular markers that are the basis for diagnosis and treatment (Louis et al., 2021). In this complicated diagnostic scenario, Magnetic Resonance Imaging (MRI) has played the role of a non-invasive method, the foundation, for a long time, providing an unmatched soft-tissue contrast for the visualization of a tumor's location, its size, and other phenomena such as the formation of edema and the push on surrounding structures, aka mass effect. Traditional MRI sequences (T1-weighted, T2-weighted, FLAIR) and advanced techniques (perfusion, diffusion, spectroscopy) produce a vast and multi-parametric dataset that is crucial for clinical decision-making (Martucci et al., 2023).

Despite the remarkable capabilities of Magnetic Resonance Imaging (MRI) in visualizing brain tumors, the interpretation of these complex images by human experts remains inherently subjective and labor-intensive. Radiologists must rely on their experience and visual acuity to analyze subtle variations in signal intensity and anatomical features, which can lead to variability in assessments and potential diagnostic inconsistencies. Moreover, this manual approach is limited in its ability

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to fully harness the vast array of quantitative data embedded within each pixel of the image. Over the past decade, a transformative shift has occurred with the integration of artificial intelligence (AI) and data science into neuro-oncologic imaging workflows. These technologies offer the potential to automate image analysis, reduce inter-observer variability, and extract high-dimensional features that are often imperceptible to the human eye. Initially applied to basic tumor detection tasks, AI algorithms have rapidly evolved to perform highly specialized functions. These include pixel-wise segmentation of distinct tumor sub-regions such as enhancing tumor tissue, necrotic core, and peritumoral edema, which are critical for treatment planning and monitoring. Furthermore, AI models are now capable of histological classification, predicting key molecular markers like IDH mutation and 1p/19q co-deletion, and even forecasting patient survival outcomes and response to therapy (Bathla et al., 2024; van der Voort et al., 2023).

At the very start of this highly active and innovative field, a large number of studies scattered all over the place indicated its dynamism and innovation. The researchers, who are trying to get an overall picture of what is going on, however, are facing a hurdle that the very same studies have caused. Systematic reviews have been done on sub-tasks like tumor segmentation (Ranjbarzadeh et al., 2022; Ul Abidin et al., 2024) and classification algorithms (Kaifi, 2023) but these have been very limited to see only a small part of the entire research ecosystem. Thus, the holistic and quantitative synthesis that portrays the total size and the evolution of the scholarly contributions in this area continues to be a large gap. The field of scientometrics, on the other hand, is a powerful methodological framework that has the potential to fill the gap. Scientometrics, which is the measurement and analysis of the scientific literature, allows the researchers to map systematically the intellectual trends, point out the influential publications and discover the collaborative networks. The current research, using scientometric techniques on a carefully selected corpus of 200 seminal articles, aims at shedding light on the structural and thematic contours of the research landscape. A data-ground overview that not only guides future studies but also encourages strategic development in the field of neuro-oncologic imaging is the vision of this research.

1. Identify the best influential researchers, institutions, and countries driving this field.
2. Uncover the most important thematic clusters and trace their evolution over the 2021-2025 period.
3. Analyze the cooperation networks that underpin scientific progress.
4. Synthesize the prevailing techniques and highlight emerging trends.
5. Provide a pillar roadmap for new authors and detect critical gaps for future investigation.

2. Methodology

2.1. Data Collection and Preprocessing

The dataset for this analysis was produced on November 3, 2025, by exporting 200 articles from the Scopus database, a leading abstract and citation database of peer-reviewed literature. The search query was designed to capture the core intersection of the field: (TITLE-ABS-KEY (MRI) AND TITLE-ABS-KEY ("brain tumor") AND TITLE-ABS-KEY ("data science" OR "data analysis" OR "AI")). The search was limited to papers published from 2021 onwards to capture the most recent and active period of research. The export included complete bibliographic records for each article, comprising titles, authors, affiliations, abstracts, keywords (both author-defined and Scopus-indexed), citation counts, source publication, digital object identifier (DOI), and references.

2.2. Analytical Framework

The research methodology used was a combination of bibliometrical quantitative followed by qualitative content analysis.

- **Descriptive Scientometrics:** This was the exercise of frequency and utility. The targeted metrics are:
    - **Publication and Citation Analysis:** Annual publication volume and the identification of highly cited papers (citation counts were obtained directly from Scopus).
    - **Author and Affiliation Analysis:** The occurrence of authors was noted as one way to point out the main writers. The affiliations of institutions and countries were analyzed in order to depict the geographical and institutional centers of research activity.
    - **Journal Analysis:** Ubiquitous-sizing of public channels that are most integral; providing the dissemination world for the aforementioned area of study.

- **Thematic and Conceptual Analysis:** It was this quality aspect that sought to capture the "what" and "how" of research.
    - **Keyword Co-occurrence:** Author keywords and index keywords were analyzed for frequency. Recurring terms like "Deep Learning," "Explainable AI," and "Radiomics" were identified as major thematic pillars.
    - **Content Analysis:** Reading and analyzing the abstracts and, for highly significant papers, the full texts of the most cited and frequently published works was a very important process in understanding the context of citations; for instance, it was possible to tell whether a paper was cited because of a new methodology, a complete review, or a large-scale validation study.
- **Network Analysis (Implicit):** Inferred collaborative networks through the analysis of co-author communication and geographical diversity of author groups in prestigious publications, even though sophisticated network visualization tools were not applied.

3. The Landscape of Production and Impact

3.1. Publication Trends and Core Outlets

The annual distribution of the 200 articles indicates a consistently high output from 2021 to 2025, implying that the application of AI to brain tumor MRI is a mature and sustained research front, not a fleeting trend. The field is disseminated through a mix of high-impact specialized journals and broader multidisciplinary platforms. Prominent outlets include *Cancers*, *Scientific Reports*, *IEEE Access*, *Biomedical Signal Processing and Control*, and *Computer Methods and Programs in Biomedicine*. This reflects the field's dual identity, straddling clinical neuro-oncology (*Cancers*, *Neuro-Oncology*) and technical computer science and engineering (*IEEE Access*, *Neural Computing and Applications*).

3.2. Intellectual Pillars: The Most Influential Works

Citation count serves as a proxy for intellectual influence and utility. The analyzed corpus contains several works that have become foundational references.

Seminal Reviews: Ranjbarzadeh et al. (2022) conducted a comprehensive review and titled it "Brain tumor segmentation of MRI images: a comprehensive review on the application of artificial intelligence tools." It has reached an impressive 233 citations, which is a sign that the paper has a strong influence and is relevant to both the neuroimaging and AI communities. The systematic and organized structure of the review is one of its major strengths as it classifies the various AI techniques for brain tumor segmentation in detail. The review does not restrict itself to deep learning-only methods, which have been the most-used techniques in research recently; it includes traditional machine learning methods like Support Vector Machines and Decision Trees in the discussion as well. Moreover, the review looks into clustering algorithm methods like K-means and Fuzzy C-means that play a key role in unsupervised segmentation tasks. The paper also takes a step back and talks about the basics of image processing that are the foundation for so many AI-based workflows. By providing a broad classification of these various methods and specifically mentioning their roles and applications in segmentation tasks, the paper is beneficial for different groups of people. It makes for new comers to the field an easy and thorough entry not only for them but also for experienced researchers who will use it as a reference manual. The review has done a great job in portraying the problem space and providing strategic solutions that are beneficial to academic discussion as well as practical implementation.

Benchmarking and Comparative Studies: Detection from MR Images Using Deep Learning Networks" is compiled with 234 citations and is staunchly positioned in the middle of empirical benchmarking necessity. It is true that the whole world is going through a continuous stream of new architectures right in this area thus, the careful comparison studies would be the most useful and dependable method of obtaining information. This paper probably conducts a thorough assessment of several CNN architectures (e.g., VGG, ResNet, Inception) using standardized datasets and reporting on different metrics such as accuracy, Dice score, and computational efficiency. This kind of study not only facilitates the community in the selection of the right techniques but also saves time by doing away with parallel experiments, thus, the whole process of establishing performance baselines becomes quicker.

Hybrid Methodological Frameworks: Rehman et al.'s study (2021) titled "Brain tumor segmentation using K-means clustering and deep learning with syn-thetic data augmentation" with (218 citations) is proof of the effectiveness of hybrid methods. It ingeniously fuses the unsupervised capability of K-means++ clustering for initial region proposal with the deep VGG19 network's final discriminative classification capability. Also, it magnificently handles the problem of small medical datasets through synthetic data augmentation. The paper's power lies in the presentation of a practical, end-to-end pipeline

that is both efficient and economically feasible to implement, thus becoming a frequently cited source for segmentation accuracy-improving studies that do not want to rely solely on monolithic deep learning models.

Performance-Optimization Strategies: Younis et al. (2022) and their work on "Brain Tumor Analysis Using Deep Learning and VGG-16 Ensembling Learning Approaches" (205 citations) highlight a crucial strategy beyond single-model design: ensemble learning. By combining the predictions of multiple VGG-16 models, the authors showed a reliable path to reach a higher accuracy and robustness than any single model could provide. They underscored a key insight in applied AI—that strategic combination of existing models may often yield bigger gains than the pursuit of a marginally better novel architecture. Its high citation count broadcasts the community's appreciation for research that provides clear methodologies for enhancing performance and reliability, a critical step towards clinical deployment.

Clinical Integration and Validation: A landmark study by **Vollmuth et al. (2023)**, "Artificial intelligence (AI)-based decision support improves reproducibility of tumor response assessment in neuro-oncology," published in *Neuro-Oncology* and cited 38 times, represents a pivotal step from lab to clinic. It built an international multi-reader investigation indicating that an AI-based decision support system could significantly contribute to the reproducibility of RANO (Response Assessment in Neuro-Oncology) criteria application among neuroradiologists. This research paper is influential not for a novel algorithm, but for its concentration on a real-world clinical problem—inter-observer variability—and its rigorous demonstration of AI's value as a clinical decision support tool, thereby constructing a compelling case for its integration into standard workflow.

4. Major Research Themes: A Deep Dive

The intellectual content of the field can be organized into several dominant and interconnected thematic clusters.

4.1. The Deep Learning Core: Evolving Architectures for Segmentation and Classification

This is the basic building block of the area. Convolutional Neural Networks (CNNs) still constitute the primary architecture for most applications. The U-Net model with its distinctive encoder-decoder style and skip connections, e.g, (Ronneberger et al., 2015), is the most commonly accepted method for segmentation tasks as it has been extensively used and even modified in several studies (Ottom et al., 2022; Nham et al., 2023). For the purpose of classification pre-trained models such as ResNet, VGG, Inception, and more recent EfficientNet, are extensively applied using transfer Learning (Sharma et al., 2023; Asif et al., 2022).

The progression can be seen in the extravagant sophistication of model designs. The primary attempts, for instance, in the case of Remzan et al. (2022), where standard CNNs were used and the baseline was set were soon followed by more elaborate (Hekmat et al., 2025) ways. Besides, the latter very skilfully combine the Chirplet Transform and the Discrete Wavelet Transform in order to produce the MRI samples that would be input for a classifying neural network, that they already perform so well since the data input is more varied. In like manner, Khan et al. (2025) apply metaheuristic optimization, to be precise, the Manta-ray Foraging Optimization algorithm, to hyperparameters of a deep residual network, which is a state-of-the-art method in automating model optimization for multi-class classification.

4.2. The Imperative of Transparency: The Rise of Explainable AI (XAI)

The increasing complexity of deep learning models led to their “black box” property becoming a significant hurdle to clinical acceptance. The reluctance of physicians to put their trust in a system whose reasoning is not accessible to them has been the driving force behind the quick development of XAI as an important topic in research. Making AI models disclosed and understandable is the end of the XAI project by supplying visual or textual justifications for the predictions made by the models.

The terms "Explainable AI," "Grad-CAM," "LIME," and "SHAP" have already become standard in the field. Zeineldin et al. (2022) did pioneering research focusing on the explainability of deep neural networks for MRI of brain glioma analysis. They utilized different XAI methods to figure out the image properties that the models relied on for making decisions like tumor classification and genotype forecasting, thus granting significant understanding of model behavior and possible error modes.

The emphasis on explainability is now being implemented right at the core of the new architectures. In particular, Nazir and co-workers (2024) created a specific CNN model that predicts brain tumors through imaging and combined several XAI techniques (Grad-CAM, LIME, SHAP) for providing visual and textual explanations that are only too comprehensive for the classification of the model. In a like manner, Ullah et al. (2024) in their "BrainNet" framework for multimodal classification is incorporating explainability for the fusion of information from different MRI sequences to be recognized and validated by a human expert. This early stage XAI integration indeed signifies the coming of age of the field as it progressively admits that the only criterion for being real-world impactful is not just performance.

4.3. Beyond Detection: Radiomics and Predictive Oncology

Radiomics has undergone a major transition from qualitative to quantitative data mining. The medical images are subjected to a very high-speed extraction of hundreds of quantitative features (which indicate texture, shape, and intensity). The characteristics that are sometimes not visible to the naked eye are then fed to machine learning models to generate either predictive or prognostic models. This topic certainly puts the area of research right into the territory of personalized medicine. The highly reputed publication of Fathi Kazerooni and colleagues (2022) exemplifies this very well. It was shown that the combination of the clinical measures, radiomic features obtained from multi-parametric MRI, and genomic data together increased the chance of survival days for glioblastoma patients. The "multi-omic" strategy exemplifies the capability of combining imaging with other biological data layers in order to build strong prognostic biomarkers. Radiomics has also been used to make non-invasive predictions about molecular information, a solution called "virtual biopsy." In a thesis by Pasquini et al. (2021), the case was made that different machine learning models would be able to predict equally well for outcomes and molecular subtypes in high-grade glioma using MRI-based radiomics. Chauhan et al. (2021) used MRI characteristics to predict the mutation status of H3K27M in diffuse midline gliomas, which is an important diagnostic and prognostic marker. These investigations are the ones that illustrate the capability of AI in lowering the number of invasive surgical biopsies and thus facilitating the proper treatments.

4.4. The Whole is Greater: Multimodal Data Fusion

The brain tumor microenvironment is heterogeneous, and no single MRI sequence can capture its full complexity. The fusion of multiple data streams is therefore a powerful and logical trend. This can involve:

- **Multi-parametric MRI Fusion:** The incorporation of T1, T2, FLAIR, T1-post-contrast, DWI, and PWI sequences to give a complete picture. Razzaghi et al. (2022) dedicated their work to "multimodal brain tumor detection using multimodal deep transfer learning," proposing techniques capable of effortlessly fusioning data from various modalities.

- **Cross-Modal Fusion:** The combination of MRI with different imaging techniques is one of the options considered, for instance, the Positron Emission Tomography (PET) that is mentioned in this research paper. Santo et al. (2022) performed a review and concluded that the use of PET scans of amino acids in combination with MRI would be helpful in distinguishing the glioma recurrence from treatment-related changes, which is a major clinical issue.

- **Clinical-Imaging Fusion:** The study conducted by Fathi Kazerooni and colleagues (2022) showed that the integration of imaging radiomics with clinical data (age, performance status), and genomic data represented the most comprehensive method for prediction.

Ullah and his colleagues (2024) who were the ones to properly give their model the name "BrainNet" pointed out its conception as a fusion-assisted methodology which comprises the use of residual blocks and stacked autoencoders for the integration of multimodal MRI data in a very efficient manner. The evolving of very complex fusion architectures is a trend that plays a significant role in the realization of more precise and clinically applicable instruments.

5. Geographical and Institutional Collaboration Networks

The research landscape is decidedly global, with distinct but interconnected hubs of activity.

- **Asia:** A powerhouse of algorithmic innovation. **China** (with institutions like Central South University and Xi'an Jiaotong University) and **India** (with institutions like IILM University, JAIN University, and Galgotias University) are prolific contributors, producing a vast number of papers on novel deep learning architectures, optimization techniques, and hybrid models. **Pakistan** (notably HITEC University) maintains a strong presence, with researchers like Muhammad Attique Khan frequently publishing on complex topics like multimodal fusion and XAI.

- **Europe:** A pioneer in clinically oriented and translational research. **Germany** is specifically prominent, with a “Heidelberg-Mannheim-Cologne” axis involving Universitätsklinikum Heidelberg, the German Cancer Research Center (DKFZ), and Universitätsklinikum Köln producing high-impact work on glioma molecular subtyping, treatment response assessment, and radiomics (e.g., Heuer et al., 2024; van der Voort et al., 2023). Italy and the United Kingdom also have strong contributions, often focused on advanced MRI techniques and radiomics.

- **North America:** Contributes from both deep technical and clinical perspectives. Institutions like the **University of Pennsylvania** (e.g., Fathi Kazerooni et al., 2022) and **Stanford University** are at the forefront of integrating radiomics with genomics and conducting large-scale validation studies.

One of the most frequent and uplifting developments is international partnership. Author teams consisting of computer scientists from Asian universities, clinical neuro-oncologists, and radiologists from Europe or North America are often seen working together. The cooperation between the technical proficiency and the clinical understanding is a critical requirement for creating tools that are not only computationally extraordinary but also medically applicable and tested.

6. Limitations of the Present Research and Critical Gaps

There are several persistent limitations and critical gaps in the current research landscape, as Patrick Ndlovu, who has a background in publishing and freelance writing, has drawn attention to in his piece on the recent scientometric analysis.

- **The Dataset Bottleneck:** Numerous studies, especially those with high citations, have their findings based on a small selection of data that is publicly available, such as the BraTS (Brain Tumor Segmentation) challenge data, which is one of the examples. The usage of these datasets, which are selected and processed, for training models has the disadvantage that such models do not perform well on the more diverse and "messy" clinical data met in practice, where there are differences in scanners, protocols, and patient groups.

- **The Clinical Translation Chasm:** The gap between the production of algorithmic papers and the prospective demonstration of clinical utility, however, is considerable. Most studies still report technical metrics (such as Dice score or accuracy) without referring them to clinically meaningful endpoints. Impact on surgical planning, radiation therapy targeting, and overall patient survival are potential clinically meaningful endpoints that could be mentioned. Vollmuth et al. (2023) are already leading the charge, however, and other similar papers may follow.

- **Methodological Reproducibility:** It is the case that numerous proposed models are intricate "one-off" solutions. The ones, however, that are not coupled with completely reproducible code, trained models, or detailed hyperparameters have such difficulties as, for example, they do not allow independent validation and thus gradually slow down the progress of science.

- **Neglect of Computational Efficiency:** Accurate predictions of the highest quality are usually accompanied by large model sizes and high computational requirements as a trade-off. Rarely, to mention the study of Shelatkar et al. (2022) that suggested a "light weight deep learning model," are researchers done to focus on the development of models that are efficient and can be deployed on everyday hospital hardware or low-end devices.

7. Conclusion and Future Directions

This enlarged scientometric review covers a discipline that is dynamic and growing rapidly at the same time. The path has evolved from showing the basic usability of CNNs to dealing with human-centered issues of model interpretability, prognostic accuracy, and multimodal integration, which are the complex ones. The influence of ground-breaking review papers, combining novel methods, comparative studies applying high standards, and trials for clinical validation having been the most influential and winning ones, has all together defined the present-day research agenda.

Looking forward, the trajectory points toward greater integration, validation, and practicality:

1. **Federated Learning for Privacy-Preserving Collaboration:** Federated learning will be one of the major methods to solve the problem of the data bottleneck without the need to pull together sensitive patient information. In this case, the different parties will be able to train the models together based on their respective local data without actually exchanging the data, which in turn will lead to the creation of more powerful and universally applicable AI tools.

2. **Prospective Validation and Randomized Trials:** Shifting from retrospective studies to prospective clinical trials is the next step. Randomized controlled trials in which clinical outcomes for patients diagnosed with AI support are compared with those of standard care will be the decisive test for these AI systems.

3. **Development of Lightweight and Deployable Models:** Research dedicated to accuracy alone is now considered insufficient, and the focus on efficiency is becoming more and more pressing. One of the most important steps in overcoming the barrier of the clinical workstations in terms of their performance is developing small and light models that are able to run in real time without losing their accuracy.

4. **Integrated Diagnostic Platforms:** The upcoming times will be the times of integrated platforms that mix the AI-based image analysis with electronic health records, genomic data, and digital pathology in complete harmony. This will not only give the whole five senses and the multi-scale aspect of the patient's dis-ease but also, undoubtedly, make precision neuro-oncology a reality.

The analysis done here, by mapping out the history and current state of this very active sector, gives a guide to the researchers, clinics, and money givers on how to go in the future. It is time now to change the main concern from just creating better algorithms to making these very powerful tools get to the patients and doctors that need them most in a reliable, transparent, and efficient way.

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