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# Deep Learning Techniques for MRI-Based Brain Tumor Analysis: A Comprehensive Review

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**Abstract**
Brain tumors are one of the most serious neurological diseases that need an early and correct diagnosis to make the right treatment plan and consequently increase the survival of the patient. The latest breakthroughs in MRI have led to the acquisition of the images of brain structures at a very high resolution but still the manual analysis of these images is a very long, subjective, and error-prone process. The deep learning (DL) methods have been introduced as a very effective tool for automatically detecting, segmenting, and classifying brain tumors in such case. This review gives a thorough discussion of the latest studies (2023-2025) utilizing deep learning methods on the analysis of brain tumors through MRI. It details convolutional neural networks, U-Net family variations, models based on Transformer architecture and hybrid networks tailored for tumor detection, grading, segmentation, and prognosis prediction. The public benchmark datasets like BraTS and multi-institutional MRI datasets are also discussed. Though very high accuracies have been reported, the studies reveal challenges such as the models being very limited in their generalization abilities, heterogeneous data, lack of interpreted results, and no thorough clinical validation. This review highlights the main trends, pros and cons, and at the same time, it points out the unexplored questions in research direction for the next generation of brain tumor diagnosis systems that will be solid, understandable, and usable in the clinic.

**Keywords**: Brain Tumor Detection, Deep Learning, MRI Image Analysis, Tumor Segmentation, Computer-Aided Diagnosis etc.

## 1. Introduction

Brain tumors, being one of the most complicated and perilous nervous system illnesses, are commonly diagnosed at a very late stage which eventually results in marked cognitive impairment, inability to work, and sometimes death. The first and foremost tumor identification and characterization step in the treatment plan includes discussion of surgery, radiotherapy, and chemotherapy. MRI is indeed the most preferred imaging technique for brain tumor diagnosis because of its excellent soft-tissue contrast and the great anatomical and functional information that it is able to deliver. Nevertheless, the increasing volume and complexity of MRI data have made it increasingly challenging, time-consuming, and error-prone [1] to manual interpretation due to the variability between observers.

The standard diagnostic techniques are mainly based on visuals from skilled radiologists, which, in turn, can be influenced by fatigue and personal judgment, etc. Besides that, the tumors also display a wide range of variability in terms of MRI characteristics like size, location, texture, and intensity patterns in different MRI sequences. Thus, such cases are a headache for manual diagnosis and even small-scale clinical settings administering routine checks. The medical imaging datasets are only getting larger, and this conflicting trend has led to a situation where automated and intelligent diagnostic systems that can help the rapidly increasing number of clinicians to make fast and reliable decisions have become a necessity [2].

Over the past few years, deep learning (DL) methodologies have turned into the most powerful instruments for medical image processing, enabling automatic feature extraction and outperforming the traditional machine learning methods significantly. Among the various deep learning architectures, Convolutional Neural Networks (CNNs) have been the most powerful, directly learning from raw MRI data [1] and being able to classify, detect and segment tumors better. U-Net and its variants have been the leading methods for brain tumor segmentation thanks to their capability to maintain spatial context and capture very small structural differences [4]. The most recent development has been Transformer-based and hybrid CNN–Transformer models which have attracted researchers as they can overcome the problem of long-distance relationships in imaging and thereby improve the quality of imaging even in the most complex scenarios [2], [5].

Segmentation has been the main subject of deep learning for brain tumor research and this has come to be the case primarily because segmentation is the basis for the volume estimation of the tumor, its treatment planning, and disease monitoring. The importance of public benchmark datasets such as the Brain Tumor Segmentation (BraTS) challenges is undeniable as they have been the main source of motivation in the development of segmentation research through the provision of standardized data and evaluation protocols [6], [10]. Although the models that are at the cutting edge of technology show great performance on these benchmarks, their accuracy often drops when the models are applied to data from other hospitals mainly due to differences in scanners, protocols and population [1], [6].

Apart from segmentation, deep learning has already made a big difference in the tumor class and grade determination. The models that were trained on the multi-class MRI datasets could easily distinguish glioma, meningioma, pituitary tumors, and also normal brain tissues with very high accuracy [7]. The combination of transfer learning and data augmentation, particularly when the amount of labeled data is small, has enhanced the performance further. Also, recently there are studies that have been able to predict tumor grade and molecular markers straight from MRI, thus, making it possible to perform non-invasive “virtual biopsy” and supporting the precision medicine approaches [3].

On the other hand, the application of deep learning-based brain tumor diagnostic systems in clinics is still facing challenges that need to be tackled. In many cases, the studies conducted are based on small or similar datasets and do not undergo external validation, which creates doubts about their generalization and reliability [2]. Model robustness is further impaired by data imbalance, especially for rare tumor subtypes. Most importantly, the majority of deep learning models work like “black boxes” with very little interpretability and uncertainty estimation which leads to reduced clinical trust and acceptance [1], [5].

One more practical issue is the dependency on complete multimodal MRI sequences, which leads to longer acquisition times, higher costs, and more computationally intensive processes. Also, more recently, researchers have looked into sequence-efficient models that are capable of working with a small number of MRI sequences and attaining nearly the same performance, thus making it possible for

automatic analysis to be done in busy or resource-poor clinical areas [8]. Not only that, but also self-configuring frameworks and meta-learning strategies have been introduced to enhance the adaptability from one institution to another and cut down the need for long retraining sessions [9], [12].

In short, the present literature shows a lot of progress in deep learning-based brain tumor analysis but at the same time exposes some corresponding gaps in the areas of generalization, interpretability, diversity of datasets, and clinical integration. The current assessment aims at merging the recent progress, identifying the shortcomings, and showing the future paths of the research that are necessary for the creation of brain tumor diagnostic systems that are reliable, interpretable, and suitable for clinical use.

## 2.Problem Identification

- If detected at an advanced stage, a tumor of the brain may lead to death; the first symptoms, however, are often nonspecific even for those close to the individual.
- The entire process of coming up with a diagnosis manually through MRI/CT scans is very slow, complicated, and less accurate than humans especially in the interpretation of fine tumor characteristics.
- The huge volume of medical imaging data forces radiologists to work less and less effectively with a reduction in the quality of diagnostics.
- Tumor types can easily be confused with one another, because of their similar sizes, shapes, intensities, and locations.
- Geographical unavailability of expert doctors in rural or low economy areas results in longer timeframes for keeping aware of, and consequently, treating, diseases.
- Manual operation, unclear outcomes, and the necessity of a long run before being clinically accepted characterize the current diagnostic tools.
- Most of the existing CAD systems are to a great extent problematic in terms of applicability, speed and reliability, and thus, there is a call for the introduction of the latest deep learning-based solutions.

## 3.Literature Survey

### A)Literature Review

Dorfner et al., 2025, This review thoroughly discusses deep learning techniques for the analysis of brain tumors based on MRI, which cover detection, segmentation, classification and prognosis prediction. It points out the predominance of CNN and U-Net architectures and the increasing application of Transformer-based models. The study points to important obstacles to the clinical use of the methods proposed such as the differences in data quality and distribution between institutions, lack of preprocessing standards, inability to generalize across sites, and low explainability. The authors call for uncertainty estimation to be treated as a prerequisite in deep learning applications in clinical scenarios and that federated learning, harmonized MRI protocols, and clinically relevant evaluation metrics should be among the methods to close the gap between benchmark performance and real-world clinical deployment conditions.

Bouhafra & El Bahi, 2025, This comprehensive review analyzes a total of 60 studies that used deep learning for MRI-based detection and classification of brain tumors. The analysis covers studies from the years 2020 to 2024. The review includes technologies such as CNNs, autoencoders, attention mechanisms, Transformers, and hybrid architectures. The review mentions that while high accuracy in

classification was achieved for several tumor types, it also pointed out serious limitations such as small dataset sizes, no external validation, class imbalance, and low explainable AI techniques. Future research directions proposed by the authors are multimodal MRI fusion, robustness to domain shift, interpretable models, and clinically oriented benchmarks which would help to improve both reliability and adoption.

Yang et al., 2025, The current research put forward the deep learning models based on MRI that can predict the characteristics of diffuse glioma prior to operation. Multiparametric MRI allows the models to predict the tumor grade and the molecular markers that are relevant for prognosis and treatment planning. The outcome reveals a high strength of the correlation between the model's predictions and the histopathological results, which allows the non-invasive “virtual biopsy” technique. The proposed method outstrips the traditional radiomics and clinical-only approaches in terms of predictive performance. The study draws attention to the potential of deep learning in precision neuro-oncology, at the same time, pointing out the necessity for AI to be trained on large multicenter datasets and to have standardized imaging protocols to lessen bias.

Verma & Yadav, 2025, The review critically evaluates deep learning methods for brain tumor segmentation. It thoroughly describes U-Net 2D and 3D variants, attention mechanisms, multi-scale feature fusion, and models enhanced by Transformers. The authors evaluate the effects of architectural design choices, loss functions, patch strategies, and data augmentation on the robustness and accuracy of the segmentation boundaries. The review includes performance evaluations on BraTS datasets as well as clinical issues like noisy labels, post-surgery imaging artifacts, and small tumor detection. The authors’ last word is that segmentation accuracy can reach high levels in benchmarks, but real-world robustness and interpretability are still unresolved issues.

Abidin et al., 2024, The future research presents a thorough examination of the recent advancements in the deep learning-based models for brain tumor segmentation from the analysis of various MRI modalities (T1, T2, T1ce, and FLAIR). It classifies the techniques into three groups, viz., CNN-based, hybrid CNN-Transformer, and attention-driven architectures. The results obtained from the research clearly indicate that the use of multimodal fusion has a very positive impact on the segmentation of tumor core and enhancement regions, however, it comes with an increased computational requirement and acquisition complexity. Data imbalance, variability of scanners, restricted generalization, and absence of uncertainty quantification continue to be the main obstacles in this area. In this respect, the corresponding authors suggest that the future study should focus on the areas of weakly supervised learning, sequence-robust models, and explainable AI for clinical application.

Bonato et al., 2025, The present review scrutinizes the progression of the BraTS datasets from 2012 to 2024, pointing out the differences in size, quality of annotations, imaging techniques, and difficulty of tasks. The paper shows that BraTS has been a major factor in the development of deep learning-based brain tumor segmentation by providing a uniform testing ground; in this way it has enabled the whole field to make substantial progress. On the other hand, it also points out drawbacks such as the lack of diversity in participating institutions, bias due to the use of a specific type of scanner, and the non-representation of some tumor subtypes. The authors call for a more extensive coverage of different patient populations, the acquisition of data over longer periods of time, and the implementation of clinically significant tasks in order to enhance generalization and minimize the difference between the performance in challenges and in everyday clinical practice.

Wong et al., 2025, The research introduces a system for brain tumor classification that is based on convolutional neural networks and utilizes the VGG16 model pre-trained. The model assigns MRI images

of glioma, meningioma, pituitary tumors, and normal brain with a remarkable accuracy of around 99% on several public datasets. Through data preprocessing and augmentation, model performance is significantly boosted. The authors showcase the dominance of deep transfer learning over conventional machine learning methods and go on to assess class-wise metrics and confusion matrices. The research concludes that automated classification systems of this kind can be integrated into clinical imaging workflows and thus, support computer-aided diagnosis as well as alleviate the workload of radiologists.

Huang et al., 2025, The investigation presented in this paper pertains to the segmentation of brain tumors based on deep learning techniques by using lowered MRI sequences. Not relying on axial fusions, models are trained on several such as T1c-only, T1c+FLAIR, FLAIR-only, etc. It has been reported that the performance of some models using reduced sequences is very close to the full sequences. However, these models require less time and resources for scanning. The method enhances the viability of the clinical trial in a busy and resource-limited environment. The research gives a final thought that sequence-efficient deep learning models can weigh the upshot against the cost and thus making it more acceptable in clinics.

Bareja et al., 2024, This research involving several institutions assesses the nnU-Net frameworks for the automatic segmentation of tumor sub-compartments, which consist of the enhancing tumor, tumor core, and whole tumor. The researchers show that by using intensity harmonization and preprocessing, nnU-Net's self-configuring pipelines can produce very stable Dice scores across different datasets. Multi-center training and test-time augmentation contribute to the observed improvements in cross-site generalization. The study mentions the failure cases of small lesions and post-operative changes. The results point out nnU-Net as a powerful baseline for brain tumor segmentation tasks in clinical practice.

Maria Correia de Verdier et al., 2024, The present report of the challenge presents MRIs of gliomas after treatment and expert annotations plus a summary of the approaches used in the 2024 BraTS contest. It points out the trends of the 3D nnU-Net, attention, and ensemble learning being its main components. The report mentions that the lack of clarity in segmentation of post-treatment caused by the mixed lesions, resection cavities, and radiation changes results into the comparably lower performance of such tasks compared to pre-treatment ones. It argues that the use of standardized evaluation measures, public leaderboards, and multi-institutional annotations is crucial for the development of clinically relevant segmentation research.

Amna Zahoor et al., 2025, The Swin Transformer architecture is used in this research for the detection and segmentation of brain tumors in MRI imaging. The model is said to have better feature locality and long-range dependency modeling than the baselines of CNN. The Transformer-based model, after the application of image enhancement and augmentation techniques, attains a classification accuracy that is on par with the traditional methods, and exhibits very good performance in segmentation, particularly for heterogeneous tumors. Nevertheless, the authors of the paper point out that Transformers need either large datasets or transfer learning in order to stabilize their trainings. They then encourage the use of hybrid CNN-Transformer models to find a nice spot between data efficiency and performance in the case of clinical applications.

Tabassum et al., 2025, This paper precludes a meta-transfer learning methodology based on nnU-Net architectures for better brain tumor segmentation in situations where data is limited. The technique provides a quick adaptation to unfamiliar scanners and hospitals by using only a few labeled samples. The experiments admittance to superior Dice scores and boundary precision, especially for the less represented tumor types like meningiomas. Besides, the traditional transfer learning method the proposed one is faster

in convergence and better in obtaining generalization across sites. The research underlines meta-learning as a viable option for the actual launch in various medical settings through its practical implications.

**B)Literature Summary**

The use of deep learning methods for analyzing brain tumors via MRI has been a significant focal point of recent studies with substantial improvements being made in the area. Tumor detection and segmentation are still mainly reliant on CNN and U-Net based models but on the other hand, Transformers and combinations of the two types of models are being developed for better learning of contextual features. Public benchmarks like BraTS have provided a boost to the development of methodologies by offering standardized datasets and evaluation protocols. The reports show that there is high accuracy when it comes to tumor classification, segmentation, and even molecular marker prediction which can all be seen as support for non-invasive diagnosis and precision neuro-oncology. Progress in multi-modal MRI fusion, the development of self-configuring frameworks and sequence-efficient models has led to better performance and increased clinical viability. However, the majority of the methods are dependent on specially curated datasets and controlled environments and only a few have been validated across different institutions. The reviews have consistently pointed out the challenges of data inconsistency, class imbalance, lack of interpretability, and insufficient clinical integration. All in all, deep learning has proven to be a powerful tool in the area of brain tumor diagnosis but it still has to go through a certain refinement before becoming robust enough for real-world deployment.

**C)Research Gap**

Even though the outcomes are quite promising, there are still many issues to be dealt with in deep learning–based brain tumor analysis research. Almost all the models are unable to generalize well to different clinical situations because of the variations in the scanners used, differences in the protocols, and the lack of demographic diversity in the training datasets. The lack of external and prospective validation further diminishes the trust in the clinical setting. A number of deep learning systems invariably operate as black boxes and provide very little interpretability and uncertainty estimation that is detrimental to the acceptance of these systems by clinicians. Also, the problem of data imbalance is still bothering the researchers, especially with regards to rare tumor subtypes and post-treatment cases, and it has not been dealt with adequately so far. Furthermore, the use of full multimodal MRI needs the high-quality resources and makes it impossible to apply the method in the clinical settings that are not well-resourced. The integration of deep learning models into real-time clinical workflows and decision-support systems is still very limited. These gaps must be solved in order to come up with reliable, explainable, and clinically deployable brain tumor diagnostic solutions.

## 4.Research Methodology

**A) Criteria for selecting this study:**

- This review focuses on the deep learning breakthroughs in brain tumor analysis with major emphasis on literature from 2023 to 2025.
- Only studies that corresponded to the given criteria were taken into account, such as detection, segmentation, classification, or prognosis prediction of brain tumors by the means of MRI.
- To guarantee scientific credibility, peer-reviewed journal articles, systematic reviews, and benchmark challenge reports were all included in the study.
- Deep learning architectures employing the likes of CNNs, U-Net variants, Transformers, and hybrid models were the main sources of literature that were given priority in selection.

- Studies that made use of publicly available datasets (e.g., BraTS, multi-institutional MRI datasets) were regarded as a great possibility for good reproducibility and therefore were given priority.
- Studies claiming that their approach was clinically relevant, for instance, reduced MRI sequences, non-invasive prediction or workflow efficiency, were considered.
- Works discussing limitations, challenges, and future directions were selected to pinpoint research gaps.
- The exclusion of studies that sought to apply methods that are now outdated, that did not properly validate their findings or that were based on non-MRI techniques was one of the selection criteria.

**B) Method of analysis:**

- A systematic qualitative review was carried out on the literature related to deep learning-based brain tumor analysis.
- Papers were grouped according to their objectives which are detection, segmentation, classification, grading, and prognosis prediction.
- Various model architectures were investigated namely CNNs, U-Nets, Transformers, nnU-Net, and hybrid frameworks.
- Studies were compared regarding the datasets, MRI modalities, and preprocessing strategies used.
- Performance metrics like accuracy, Dice coefficient, sensitivity, and robustness were evaluated wherever reported.
- Clinical applicability was analyzed covering issues like generalization, interpretability, and computational efficiency.
- The studies were compared for their common strengths, limitations, and methodological trends.
- The results were synthesized to pinpoint the research gaps and future opportunities for the integration of brain tumor diagnosis systems into the clinical workflow.

**C) Comparison and Analysis:**

| Reference (Year) | Method / Model Used | Dataset / Imaging Type | Key Strengths |
|---|---|---|---|
| Dorfner et al. (2025) | CNN, U-Net, Transformers (Review) | MRI, BraTS, Multicenter | Comprehensive overview; highlights clinical translation issues |
| Bouhafra & El Bahi (2025) | CNN, AE, Attention, Transformers | MRI (Public datasets) | Systematic taxonomy of DL models |
| Yang et al. (2025) | CNN-based DL | Multiparametric MRI | Non-invasive prediction of glioma biomarkers |
| Verma & Yadav (2025) | U-Net variants, Hybrid DL | BraTS MRI | Detailed segmentation architecture analysis |
| Abidin et al. (2024) | CNN–Transformer, Attention DL | Multimodal MRI | Improved segmentation accuracy using multimodal fusion |
| Bonato et al. (2025) | Dataset Review (BraTS) | BraTS MRI (2012–2024) | Dataset evolution and benchmarking insights |

| Reference (Year) | Method / Model Used | Dataset / Imaging Type | Key Strengths |
|---|---|---|---|
| Wong et al. (2025) | VGG16 CNN | MRI (Public datasets) | High classification accuracy (~99%) |
| Huang et al. (2025) | DL with reduced sequences | MRI (T1c, FLAIR) | Reduced scan time; practical deployment |
| Bareja et al. (2024) | nnU-Net | Multicenter MRI | Strong cross-site generalization |
| Tabassum et al. (2025) | Meta-transfer learning + nnU-Net | Multicenter MRI | Effective few-shot learning |

**D) Evaluation of methodologies used in the reviewed studies**

- Deep learning architectures, including CNNs, U-Net variants, and nnU-Net, are the most commonly used methods for brain tumor detection and segmentation in the majority of reviewed studies.
- The effectiveness in segmentation tasks of U-Net-based models is a direct result of their capability to efficiently capture spatial and contextual features.
- The introduction of Transformer and hybrid CNN–Transformer models positively impacts the long-range dependency modeling, yet they come with the prerequisite of large datasets.
- Public datasets, particularly BraTS, are the main source of data for many studies and facilitate standardized evaluation but, at the same time, reduce the diversity of clinics.
- Skull stripping, normalization, and augmentation are among the preprocessing techniques which have a remarkable impact on the performance of the model.
- Transfer learning is a common approach for dealing with the problem of limited labeled data; however, it can also result in the introduction of bias.
- External or multi-center validation is seldom done in studies, which consequently diminishes the generalization capability.
- Explainability and uncertainty estimation are seldom part of the methodologies.
- Many parameters that are overlooked in experimental design are computational complexity and real-time feasibility.

**E) Highlighting trends, advancements, and challenges**

**Trends**:

- Deep learning is increasingly being adopted for automated MRI analysis of brain tumors.
- CNN and U-Net variants have taken over the segmentation and detection tasks.
- Transformer and hybrid CNN–Transformer architectures are becoming more and more popular.
- Public benchmarks like BraTS are mainly used for evaluation purposes.
- The trend is moving towards multimodal MRI fusion, which brings higher accuracy.
- Sequence-efficient models are gaining attention since they help in cutting down the overall scan time.
- There is a growing interest in non-invasive tumor grading and prognosis predicting.

**Advancements:**

- Deep architectures have led to a big leap in the accuracy of both segmentation and classification.
- On the other hand, self-configuring frameworks (nnU-Net) have been developed for the purpose of robust performance.
- Meta-learning and transfer learning were employed in situations with limited data.
- Radiogenomics was incorporated for the purpose of predicting molecular markers.
- Lightweight and reduced-sequence models were used to lower the computational burden.
- Attention mechanisms and Transformers contributed to better feature learning.
- The benchmarks driven by the challenges have significantly improved.

**Challenges:**

- Variability in using different scanners and protocols results in limited generalization across institutions.
- There is an over-reliance on datasets that are very small or not very diverse.
- Deep learning models do not offer any explainability or uncertainty estimation.
- Inability to manage the imbalance between various classes and the occurrence of rare tumor subtypes.
- Training of complicated models requires a large amount of computational power.
- Clinical validation and real-time deployment are still behind.
- Integrating models into current clinical workflows is a challenging task.

## 5.Discussion

### A) Synthesis of findings from literature

The literature surveyed shows that deep learning algorithms have taken over the entire field of MRI-based brain tumor analysis, bringing almost all the traditional machine learning methods to the ground in detection, segmentation, and classification tasks with huge differences in performance [1], [2]. The use of Convolutional Neural Networks and U-Net variants has been universally recognized as the most successful design models for tumor segmentation. This is mainly owing to their imposing feature learning and boundary delineation skills [4], [6]. Lately, the developments have pointed out a gradual yet steady shift towards using Transformer-based and hybrid CNN–Transformer models, which come with the goodness of improved contextual understanding and robustness in the case of the very difficult heterogeneous tumor areas [2], [5], [11].

Standard datasets like BraTS have been important in the research process in that they have made possible the evaluation and comparison of different models by means of a common metric, thus accelerating research considerably [6], [10]. The research also indicates the development of the clinical relevance that includes the models that work with lesser sequences and thus lesser MRI acquisition requirements [8] and non-invasive tumors grade and molecular markers predicting, in support of precision neuro-oncology [3]. The use of self-configuring and adaptive frameworks like nnU-Net, along with meta-transfer learning methods, has led to an increased cross-institutional adaptability and better performance in the settings where data scarcity prevails [9], [12].

Yet, the literature has been reporting the very same challenges which are still there and are related to generalization, data heterogeneity, limited external validation, and lack of explainability. These challenges mainly hold back the deployment of AI in day-to-day clinical practice in the real world [1], [2], [6].

**B) Methodology for future research directions**

Pre-processing: Implements a series of transformations like noise eradication, contrast enhancement, and high-frequency filtering to boost MRI image quality. Tumor areas become more discernible as a result of artifact removal and intensity level adjustments.

Skull Stripping: Discards the skull part of the MRI, leaving only brain tissues. Prevention of incorrect segmentation of structures outside the brain and isolation of the area of interest are the two main benefits of this technique.

Segmentation: The principal regions of the brain are categorized into Gray Matter (GM), White Matter (WM), Cerebrospinal Fluid (CSF), and tumor. Using the methods of region-growing or thresholding, algorithms are applied to highlight the areas that are questionable.

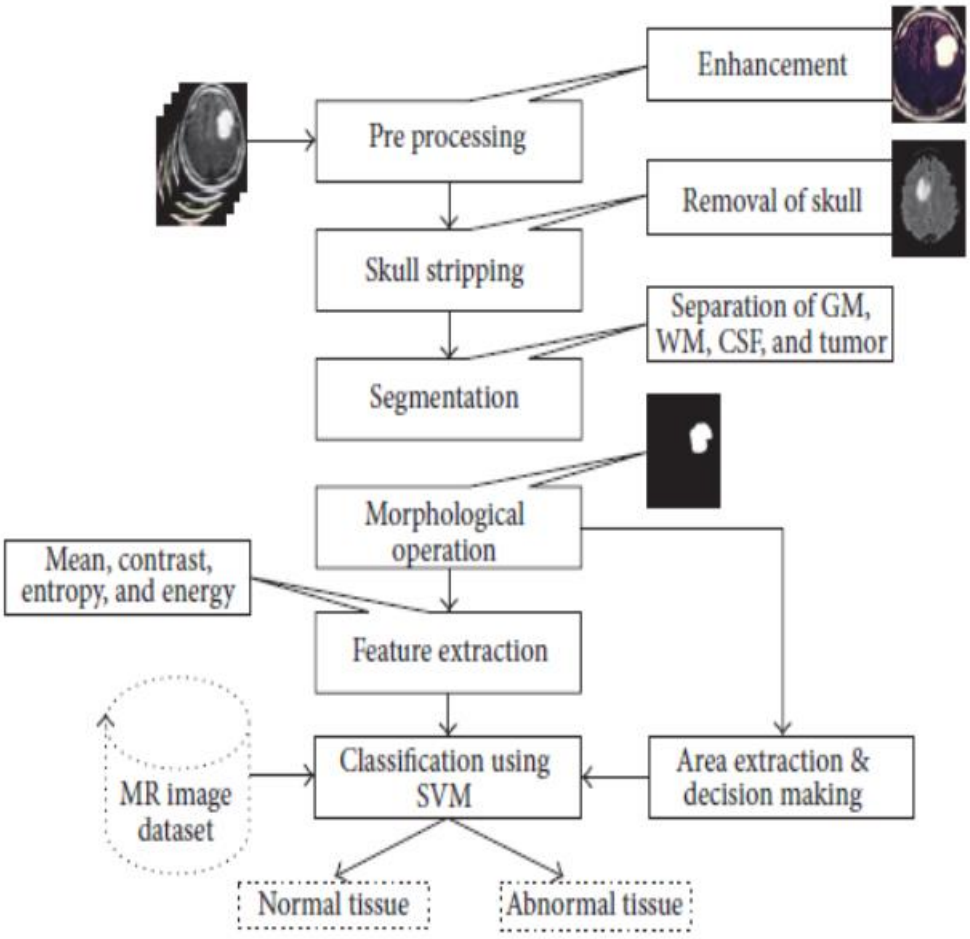


Fig.1. Predictive Analytics and Machine Learning Model

Morphological Operations: Over segmentation smoothing, small noise removal, and tumor shape enhancing apply. Polishes edges, takes off tiny noise, and makes the tumor's shape clearer.

Feature Extraction: Think of average intensity, contrast, entropy, and energy as solid features among others that are exactly the ones capable of differentiating tumor tissue from healthy tissue. These are the features based on statistics and of the texture that specifically assist in differentiating the tumor from the adjacent healthy tissue.

Classification Using SVM: Normal or abnormal tissues are classified by Support Vector Machine (SVM) classifier using the features that have been extracted. SVM measures each input feature against the knowledge-based dataset for precise classification.

Area Extraction & Decision Making: Defines tumor size, shape, and position as a diagnostic support. The classification output indicates whether the brain tissue is normal or abnormal.

## 6. Conclusion

The review reviewed the recent improvements in the application of deep learning methods for brain tumor analysis based on MRI, including detection, segmentation, classification, and prognosis prediction. The studies reviewed indicate that even though deep learning architectures, specially CNNs, U-Net modifications and new Transformer-based models, these have still led to huge performance over traditional methods. Initiatives like BraTS have set up a standard evaluation and thus speeding up the methodological progress, while methods like nnU-Net, meta-transfer learning, and reduced-sequence MRI models have made quality and clinical use better. Moreover, the progress in radiogenomics and non-invasive tumor characterization has drawn attention to the capability of deep learning to browse through and support precision neuro-oncology. To this point, despite these accomplishments there are still quite a number of major barriers that exist, preventing the routine clinical adoption of this technology. Among these barriers are the limited generalization across institutions, dependency on uniform datasets, lack of interpretability and uncertainty estimation, and inadequate prospective validation. Overcoming these obstacles will need larger multi-center datasets, standard imaging protocols, explainable AI frameworks, and even more interaction between medical and technical teams. Next, the research should emphasize on the evaluation that is of clinical importance, the real-time deployment and the workflow integration that would help in the transition of deep learning models from research benchmarks to reliable clinical decision-support systems.

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