The Original

BRAIN TUMOR DETECTION AND CLASSIFICATION IN MEDICAL IMAGING: A SYSTEMATIC REVIEW OF APPROACHES, CHALLENGES AND RESEARCH TRENDS

Sumaiya[1,*], Ranjit K N[2]

[1]Assistant professor, Department of Computer Science and Engineering, Maharaja Institute of Technology Thandavpura, summaiyakhanum@gmail.com
[2]HoD, Department of computer science and engineering, Maharaja Institute of Technology Thandavpura, hodcse@mitt.edu.in

ABSTRACT
Recently, the world has observed emerging transformations in several domains due to the crucial developments in computer vision and Artificial Intelligence (AI) such as Machine Learning (ML) and Deep Learning (DL) techniques. This revolution has also inspired the medical sector as it generates a huge range of information. Among various medical domains, these techniques have shown excellence in identifying and categorizing brain tumors using different modality images. Thereby, this research study aims to review the use of AI techniques in brain tumor detection and classification studies by using Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. This review covers the insights about the review of several AI techniques for brain tumor detection and classification approaches, concerning complicated tumor types and heterogeneous datasets. This review has also explored imaging modalities used for brain tumor analysis along with the conceptual overview on performance measures considered and experimental platforms considered for the experimentation. This analysis offered promising results to assist future researchers with a comprehensive perspective on recent research trends and analysis of several DL methodologies. Finally, it also discusses the challenges and future research directions on upcoming research challenges and opportunities for brain tumor detection techniques to assist medical professionals.

KEYWORDS: Brain Tumor Detection and Classification, Medical Imaging and Analysis, Artificial Intelligence, Machine Learning, Deep Learning, Systematic Review, Challenges and Research Trends.

1. INTRODUCTION

1.1. Background

Brain tumor is one of the diseases caused by uncontrollable cell growth in the brain, resulting in severe health problems like motor impairment and memory loss [2]. Brain tumors are characterized by abnormal proliferation of brain cells, representing the most crucial form of brain disease [6]. It has some generalized symptoms such as headaches, intracranial hypertension, and in extreme cases, indicators like sixth-nerve palsy, vomiting, and nausea are also observed [7]. Hence, early detection of brain tumors plays an essential role for extending the survival of patients [8]. However, advancing technologies like AI and computer-aided diagnosis have shown a crucial role in facilitating radiologists for earlier detection of brain tumors especially for reducing the probability of false diagnoses and reducing the manual burden to radiologists and healthcare professionals [10, 11]. Generally, radiologists use Magnetic Resonance Imaging (MRI) samples for detecting brain anomalies [13, 14]. However, the manual grading process is difficult and can lead to false-positive or false-negative results, particularly in early stage anomalies [15]. Manual errors particularly can impact survival rates for brain anomalies in individuals [18]. Recently, Deep Learning (DL)-based approaches have been employed for brain image analysis for achieving excellent results [22]. These models have the ability to handle huge scales of data, yielding promising results in several domains, especially in the biomedical area [23]. Segmentation, detection and classification are three different processes with different functionalities considered for brain image analysis. Segmentation outlines pixel-level and precise boundaries of the tumor, offering its precise size and shape. The detection process locates the existence of a tumor in images and acquired the diagnosis results whereas the classification of brain tumors finds the tumor type such as benign vs malignant categories. Thereby, this study analyzes and reviews the existing research works in the field of brain tumor detection and classification by categorizing with the AI techniques along with the estimation of theoretical concepts.

1.2 Objectives

The objectives of the SLR on brain tumor detection and classification framework are given here.

- To comprehensively analyze and compare the existing research works in the field of brain tumor segmentation, detection and classification by categorizing with the techniques used like machine learning or deep learning techniques, to revolutionize the biomedical sector.

- To provide detailed insights into different imaging modalities used for the detection of brain tumor including magnetic resonance imaging (MRI), and computed tomography (CT) images along with their advantages and disadvantages of the traditional approaches to promote future directions.
- To estimate the underlying factors of brain tumor segmentation, detection and classification models like datasets, metrics of performance, chronological analysis, along with the research challenges and gaps in existing models and the future research directions.

1.2. Research Questions

This research study covered the following research questions.

- What do Artificial intelligence-based approaches demand while examining the multimodal medical images related to neurology?
- How does the utilization of machine learning and deep learning techniques improve the medical sector in brain image analysis?
- What are all the categories of datasets, metrics, and tools utilized for the brain tumor image analysis, especially for brain tumor segmentation, detection and classification, to offer precise and early intervention and treatment options?

1.3. Chronological Analysis

The chronological analysis provides the analysis on the number of collected articles with respect to the year's distribution. Figure 1 shows the graphical representation of the chronological analysis of the acquired articles.

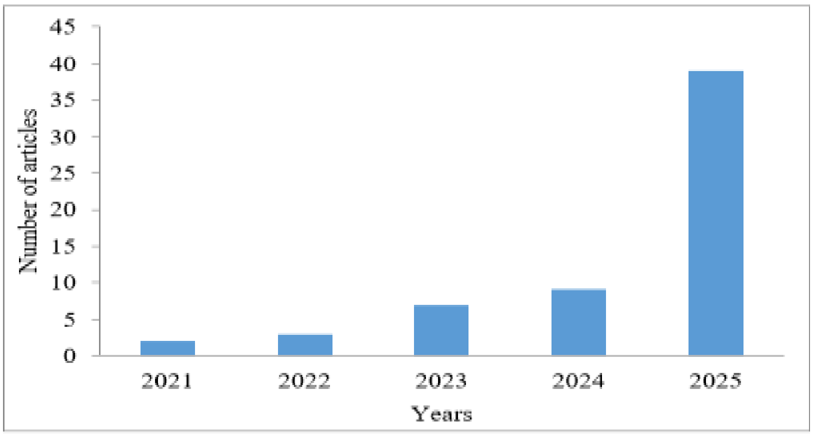


Figure 1: Representation of the number of articles published against years on brain tumor detection and classification models

1.4. Structure of the Paper

Briefly describe the layout of the paper sections. Section 2 gives the methodology for the article selection. Section 3 provides theoretic review on brain tumor detection and classification. Section 4 provides the conceptual overview on brain tumor detection and classification methods. Section 5 provides the analysis of an end-to-end deep learning framework for brain tumor. Section 6 gives the research challenges and gaps in existing models along with the future research directions. Section 7 provides the conclusion to this SLR.

2. METHODOLOGY

To acquire relevant and conventional literature works, PRISMA approach is applied in this research for meeting the objectives and formulated research questions. It is a well-described protocol, applied for ensuring a detailed and thorough analysis.

2.1. Data Sources

To ensure widespread coverage of peer-reviewed and scholarly studies, several digital databases and repositories were utilized. These include

- IEEE Xplore Digital Library
- ScienceDirect (Elsevier)
- SpringerLink
- MDPI Journals
- Wiley Online Library
- Frontiers Journals
- BMC and PLOS Journals
- arXiv (Cornell University Repository)
- Google Scholar

2.2. Search Strategy

The keywords such as ("brain tumour" OR "glioma") AND ("detection" OR "classification" OR "segmentation") AND ("MRI" OR "magnetic resonance imaging") ("deep learning" OR "machine learning") AND ("brain tumor") AND ("medical imaging" OR "radiomics") ("transformer" OR "vision transformer" OR "U-Net" OR "UNet++") AND ("MRI segmentation" OR "brain tumor detection") ("explainable AI" OR "XAI" OR "interpretable model") AND ("brain tumor" OR "neuroimaging") ("federated learning" OR "transfer learning") AND ("brain MRI" OR "medical image analysis") are applied to identify relevant studies.

2.3. Selection Criteria

The inclusion and exclusion criteria applied during the study selection process are shown as follows. The studies must be published in peer-reviewed articles or journals, written in English not older than 2019 are included. Moreover, the older journals before 2019 are excluded and also written in other languages are also excluded.

2.4. Data Extraction

The data extraction is carried out by PRISMA methodology to extract and summarize data from selected papers. The flowchart of the PRISMA methodology is given in Figure 2.

2.5. Synthesis Method

The collected articles were systematically analyzed by evaluating and screening several studies from several databases, ensuring quality and relevance. The duplicate articles are removed and irrelevant records are excluded, and the full-text articles are eligible for analysis and so, it is estimated by considering the inclusion criteria. Finally, 60 research articles are synthesized through careful analysis, depicting key AI methodologies, brain tumor detection and classification approaches.

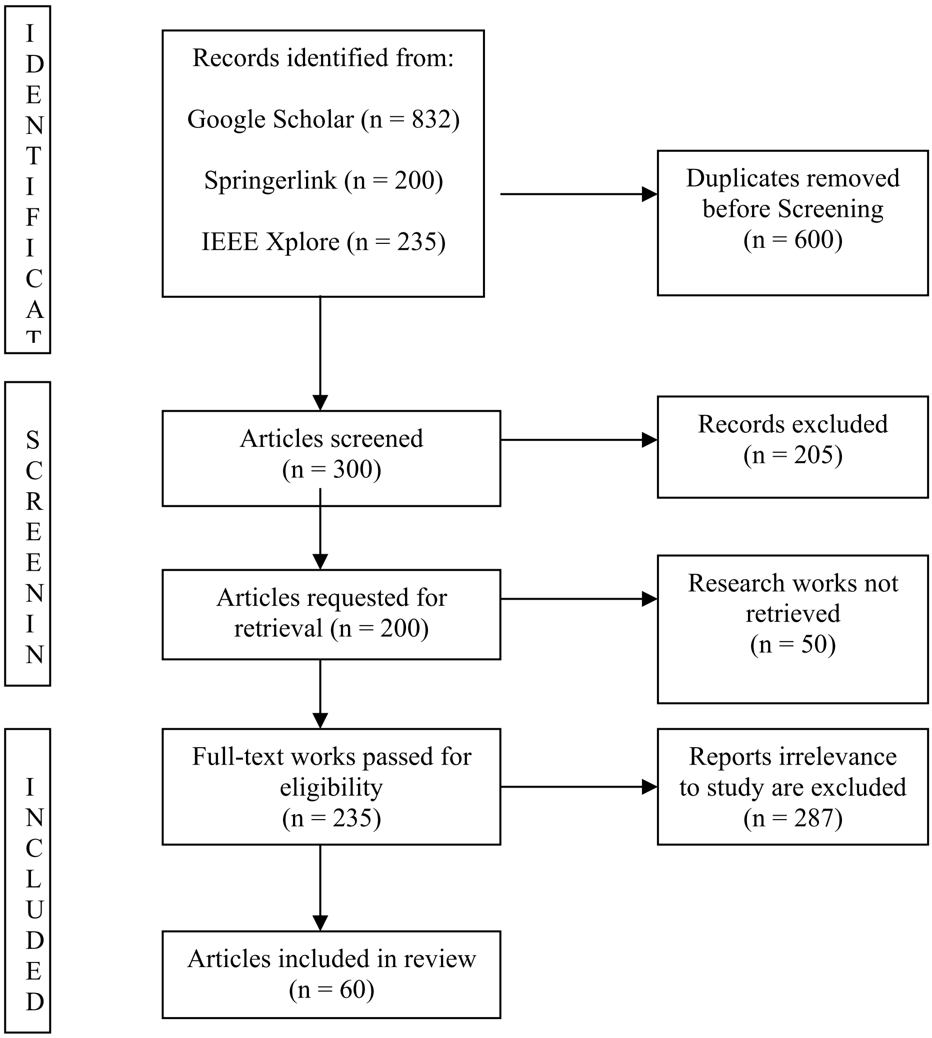


Figure 2: Flowchart of PRISMA methodology for article collection

3. Brain Tumor Detection and Classification: Theoretical Review

Existing methods on brain tumor detection and classification models using AI techniques are discussed for detailed understanding and analysis of DL techniques to learn intrinsic patterns and can acquire crucial imaging features to identify particular malignancy grades or tumor types. MRI-based brain tumor detection scheme is presented in [1] to detect classes of brain tumors such as pituitary, meningioma, and gliomas. The YOLOv7 model has precisely identified the existence and location of brain tumors and achieved a higher accuracy rate. It is achieved by integrating the Convolutional Block Attention Module (CBAM) attention scheme for enhancing features and acquiring the more suitable features correlated with tumors to assist the detection process. ResNet101 coupled with CWAM (ResNet101-CWAM) [3] is proposed for brain tumor classification to make precise clinical decision making abilities to guide precise patient outcomes and treatment schemes. MRI image-based brain tumor classification is conducted to classify tumor categories such as pituitary, no tumor, meningioma, and glioma, with higher classification accuracy. A hybrid approach using VGG16 and an attention mechanism [4] is proposed for classification of brain tumors, maximizing performance and clinical utility. It has achieved better diagnostic accuracy and also preserved clinical transparency. It also efficiently handled the mild class imbalance problem and also reduced overfitting and improved generalization. The brain tumor segmentation process is carried out in [5] by using Dual-Stream Iterative Transformer UNet (DSIT-UNet) to capture tumor boundaries and enhanced segmentation robustness by conducting multiscale feature extraction and hierarchical attention strategies. This segmentation helps in clinical neuroimaging applications especially to the 3D volumetric segmentation process. It efficiently addressed the balance of precise boundary delineation with region homogeneity. The saliency map visualization is incorporated for highlighting complicated tumor regions, which also predict clinically suitable features like internal heterogeneity patterns and tumor boundaries, building trust in medical implementation. "A CNN-VGG16-based hybrid scheme [9] is presented for brain tumor classification, to enhance diagnostic accuracy and trust in healthcare applications. An explainable AI (XAI), a method called SHapley Additive exPlanations (SHAP) is utilized for offering pixel-level attribution of model decisions, with transparent solutions to handle the black box problem, maximizing model robustness and generalizability. This method is more suitable for differentiating among several neurological diseases. The integration of Transformers' self-attention in U-Net called TransUNet [16] is proposed for segmenting brain tumor regions. It has enhanced the segmentation of small tumors and targets in the Transformer decoder. It is also required to reduce training costs and improve overall effectiveness, maintaining consistency by integrating the similar hyperparameters like batch size. Pre-trained and transfer learning models like DenseNet121, VGG16, ResNet50, InceptionV3, MobileNetV2, and Xception schemes [17] are applied for classifying brain tumors, reducing computational resources and training time along with performance maximization on enhanced cancer diagnosis. These architectures have shown their capability for acquiring intrinsic features and delivering higher accuracy in image classification works. The accurate and timely decisions are observed to support clinicians in enhancing and automating the diagnosis process. On the other hand, transfer learning approaches such as EfficientNetV2, InceptionV3, ResNet50, and VGG19 [19] models are applied for identifying both binary (abnormal and normal) and multiclass outcomes as 17 classes such as Neurocytoma, Meningioma, Glioma, and other categories of injuries like Cysts and Abscesses. The highly precise classification results were achieved and acquired superior diagnostic precision, computational demands, and model complexity. It has demonstrated optimal balance among specificity and sensitivity and so, crucial for clinical applications. ResNet50 is integrated with Grad-CAM [20] for providing precise and explainable detection of brain tumors. It has detected brain tumors in an efficient and effective way in training across several imaging environments. ResNet50 has efficiently handled the faster learning of networks and also tackled the vanishing gradient problem. It has maintained efficacy and mitigated computational complexity. The generalization capacity and performance of the proposed ResNet50 has ensured better brain tumor diagnosis model. It has enhanced interpretability influencing decision-making process. A customized CNN [21] is integrated for extracting significant features from images and the optimized XGBoost is proposed for brain tumor classification, which makes precise and transparent decision-making process. This hybrid DL-based scheme has shown precise outcomes for classifying multi-class brain tumors, enhancing the interpretability. Grad-CAM approach is further applied for visualizing the regions on the predicted model, increasing the reliability of the model. The CNN-based abnormal tissues are identified by [24] from the brain MRI images and also enhanced the overall efficiency of the classifying brain tumors. This approach has conducted brain tumor classification to improve accuracy and also handled the issue of probability of false negatives and false positives.

3.1. AI Techniques used in brain tumor detection

Different AI techniques used for brain tumor segmentation, detection and classification models are listed in Table 1.

Table 1: **DL approaches applied for existing brain tumor segmentation, detection and classification models**

References	Tumor Segmentation	Tumor Detection	Tumor Classification
[1]	-	You Only Look Once version 7 (YOLOv7)	-
[2]	-	-	-
[3]	-	-	ResNet101-CWAM
[4]	-	-	VGG16, an attention mechanism
[5]	Dual-Stream Iterative Transformer UNet (DSIT-UNet)	-	-
[9]	-	CNN-VGG16	-
[16]	TransUNet	-	-

[17]	-	-	Xception, MobileNetV2, InceptionV3, ResNet50, VGG16, and DenseNet121
[25]	nnU-Net	-	
[27]	-	-	Multi-head attention mechanism
[28]	-	-	Residual Vision Transformer (ResViT)
[29]	-	-	CE-EEN-B0 and ResGANet
[30]	-	-	DenseNet169
[32]	U-Net	-	T-InceptionNet
[33]	multiple tasking Wasserstein Generative Adversarial Network U-shape Network++ (MWG-UNet++)	-	-
[34]	-	-	GoogLeNet
[36]	3DUnet and 3DUnet Transformer	-	-
[37]	no-new-Unet (nn-Unet), and NVIDIA-net (nv-Net)	-	-
[38]	U-Net-based VGG-19	-	-
[39]	-	-	CNN
[40]	-	-	CNN and an optimized ResNet101
[41]	-	-	DenseNet121
[45]	-	-	Fully Convolutional Neural Network (FCNN) and You Only Look Once version 5 (YOLOv5)

3.2. Different Imaging Modalities

This section discusses various imaging modalities considered related to this study. MRI images are more crucial to analyze brain images as they facilitate high-resolution and detailed brain images, highlighting the visualization of tumor characteristics and morphologies. MRI scans exploit multi-dimensional information such as contrast-enhanced sequences, T1- and T2-weighted representations offering huge-range of information about internal composition, shape, size and location insights. These multi-modal imaging data offer a comprehensive imaging of the tumor, facilitating the accurate detection and classification of brain abnormalities. The utilization of MRI images with deep learning techniques provides excellent potential to enhance patient care in neuro-oncology and development of reliable and robust approaches for classification. From the analysis, MRI [1, 3, and 4], Fluid-Attenuated Inversion Recovery (FLAIR) MRI images [5] and T1-Contrast-Enhanced, & T2-weighted MRI sequences, T1-weighted, and CT scans [27] are commonly applied for brain tumor diagnosis models.

3.3. Comparative study

The comparative study on advantages and disadvantages related to existing studies on brain tumor diagnostic and classification approaches are shown in Table 2.

Table 2: Comparative study on existing brain tumor diagnostic models

References	Technique applied	Advantages	Challenges
[49]	CNN	➢ It has improved diagnostic accuracy (86%) and medical decision-making by offering explainable and transparent insights into the model detections, especially for enhanced patient care.	➢ It struggles to handle data imbalance, and is also required to improve the comprehensibility and reliability of the acquired results.
[52]	Cubic Support Vector Machine (SVM) and weighted K-Nearest Neighbors (KNN)	➢ It has achieved the highest accuracy of 99.80%, enabling brain tumor identification and reducing misdiagnosis risks owing to the integration of optimization algorithms for feature optimization and fusion.	➢ Despite its excellent performance, it observes the challenges related to overfitting, and also missed some irrelevant features chosen for classification, leading to lower efficiency and accuracy.
[53]	ResNet101, and Xception	➢ The hybrid model has efficiently captured both detailed and hierarchical features from MRI images and enhanced the accuracy rate for classification, improving consistency across several	➢ It may introduce false-positive predictions, leading to unnecessary and unauthorized medical interventions along with frightening patient emotions.

		imaging conditions and reducing the false negative rates.	
[55]	CNN with VGG16	➢ It has obtained an accuracy of 99.24%, especially while processing large scales of 17,136 brain MRI images with four different tumor classes. The created user-friendly web application has the potential to upload the images and predict the real-time tumor cases, eradicating human errors.	➢ Although the designed web application for processing the medical images exhibits higher performance, it may lead to false negative rates.
[56]	Region-based CNN architecture called Res-BRNet	➢ It observed excellent accuracy (98.22%) by optimizing the smoothness level and sharpening in harmony with the imaging spatial features and also acquired discriminative local features along with the tackling of vanishing gradient problems.	➢ However, while testing the unseen data on the designed model, it observed classification accuracy of 93.72%, which restricts the real-world performance and generalizability.
[57]	Deep Boosted Features and Ensemble Classifiers (DBF-EC)	➢ It efficiently extracted dynamic features for learning inconsistent and heteromorphic behavior of several tumors and acquired 99.56% of accuracy rate, increasing classification performance.	➢ The more detailed feature space visualization is required to estimate the large-scale dataset.
[58]	Ensemble methods	➢ The ensemble of techniques such as DeepSCAN, nnU-Net, and DeepSeg are applied for precise and automated segmentation of detection of glioma boundaries in brain medical images, revealing high-quality segmentation outcomes.	➢ However, the real-world applicability is lacking due to the lack of smaller size and complicated nature of brain tissue in pediatric patients especially for tumor tissue analysis.
[59]	Generative Adversarial Dilated Attention Convolutional Transformer (GDacFormer)	➢ It has focused on segmenting the tumor regions and also captures long-range dependencies at several scales to maximize the performance on segmentation tasks.	➢ Though it suffers from extracting the smaller percentage of brain tissues along with different sizes and shapes of brain tumors.
[60]	CNN with focal cross and self-attention transformers	➢ The proposed model has extracted characteristic input information from brain tumors and extracted local and richer semantic information to promote the segmentation efficiency in terms of dice coefficients.	➢ It limits the performance due to the lack of balance among self-attention learning ability and computational complexity.

4. Conceptual overview on Brain Tumor Detection and Classification

By analyzing the conventional methods in terms of datasets, performance evaluation measures and experimental settings, the valuable insights into the development of DL-based brain tumor diagnostic and classification approaches are acquired. It aims to discover areas, patterns and trends of enhancement in DL approaches for diagnosis. These findings will allow researchers to make informed decisions regarding brain tumor analysis, especially leading to enhanced patient care and prognosis.

4.1. Datasets

This section discusses the datasets and sources considered for the analysis. The use and availability of several and well-formulated datasets considered [12] in the existing brain tumor detection schemes are considered in this study. The quality of the dataset also plays a crucial role in final design and outcomes achieved by the AI-driven diagnosis models. Table 3 presents some of the datasets considered in the conventional diagnostic approaches.

Table 3: Analysis on the datasets and sources considered for the analysis of classical brain tumor diagnosis models

Citation	Datasets
[2]	Kaggle datasets like https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumorclassification-mri, and https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset
[3]	Kaggle MRI dataset (https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset)
[25]	BraTS 2020 dataset

[26]	Brain Tumor MRI 44c, Brain Tumor MRI 17c, and Brain Tumor Multimodal CT and MRI kaggle datasets
[28]	Public BraTs 2023, Figshare, and Kaggle datasets
[29]	Kaggle dataset
[30]	Bangladesh Brain Cancer MRI Dataset
[32]	MRI dataset comprising 485 cases
[33]	BraTS dataset 2021
[34]	Kaggle Brain Tumor MRI Dataset with 7023 images
[37]	BraTS 2021 dataset (1251 images)
[38]	The Cancer Imaging Archive (TCIA) dataset
[39]	https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset
[40]	MRI image dataset from Kaggle (https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumorclassification-mri)
[41]	Figshare, SARTAJ, and Br35H datasets ("https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset")
[45]	https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri

4.2. Performance metrics

This section discusses the performance measures considered for the evaluation. These are crucial tools offering evidence to the research works in terms of reliability and effectiveness of particular models or algorithms. Every metric has different functionality, offering deeper insights about their significance and purpose. Table 4 presents the analysis on the different measures considered in the literature.

Table 4: Performance evaluation measures considered in the literature brain tumor diagnosis models

Citation	Measures								Accuracy rate
	Accuracy	Specificity	Sensitivity	F1-score	Precision	Confusion matrix	Recall	Miscellaneous	
[1]	✓	✓	✓	✓	✓	✓	✓	-	99.5
[3]	✓	-	-	✓	✓	-	✓	Area under the receiver operating characteristic (ROC) curve (AUC)	99.83%
[26]	✓	-	-	✓	✓	✓	✓	-	97.54%
[28]	✓	-	-	✓	✓	-	✓	-	98%
[29]	✓	-	-	✓	✓	-	✓	Error rate, and Cohen's Kappa score	99.11%
[30]	✓	-	-	✓	✓	-	✓	Jaccard score	99.83%
[32]	✓	✓	✓	✓	-	-	-	ROC Curve	93.40%
[33]	✓	-	-	-	-	-	-	-	89.45%
[34]	✓	-	-	✓	✓	-	✓	Classification report	94%
[38]	✓	-	-	✓	✓	-	✓	Intersection over Union (IoU)	-
[39]	✓	✓	✓	✓	✓	-	-	-	94%
[40]	✓	-	-	✓	✓	-	✓	AUC	99%
[41]	✓	-	-	✓	✓	-	✓	ROC	97.30%
[45]	✓	-	-	✓	✓	✓	✓	ROC	98.80%

4.3. Experimental settings

The analysis on the experiment settings is crucial for the design and implementation of brain tumor detection and classification models. It involves the use of specific tools and libraries for robust visualization, modeling, statistical analysis and reliable data handling, facilitating future researchers to show the suitable platform. Figure 3 shows the experimental settings considered in the existing brain tumor detection and classification approaches. These platforms are mostly considered for the experimentation of brain image analysis, which helps the upcoming researchers.

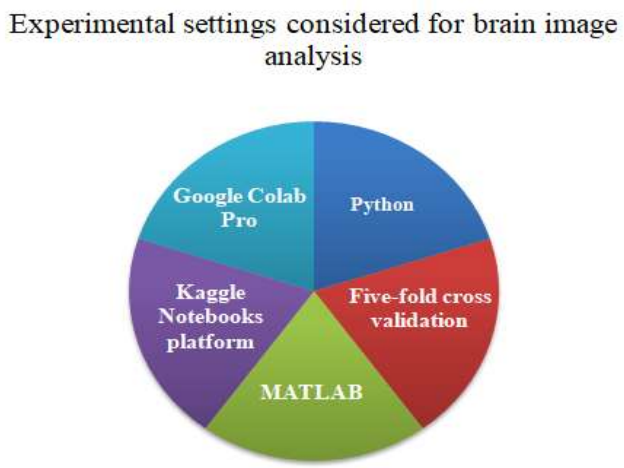
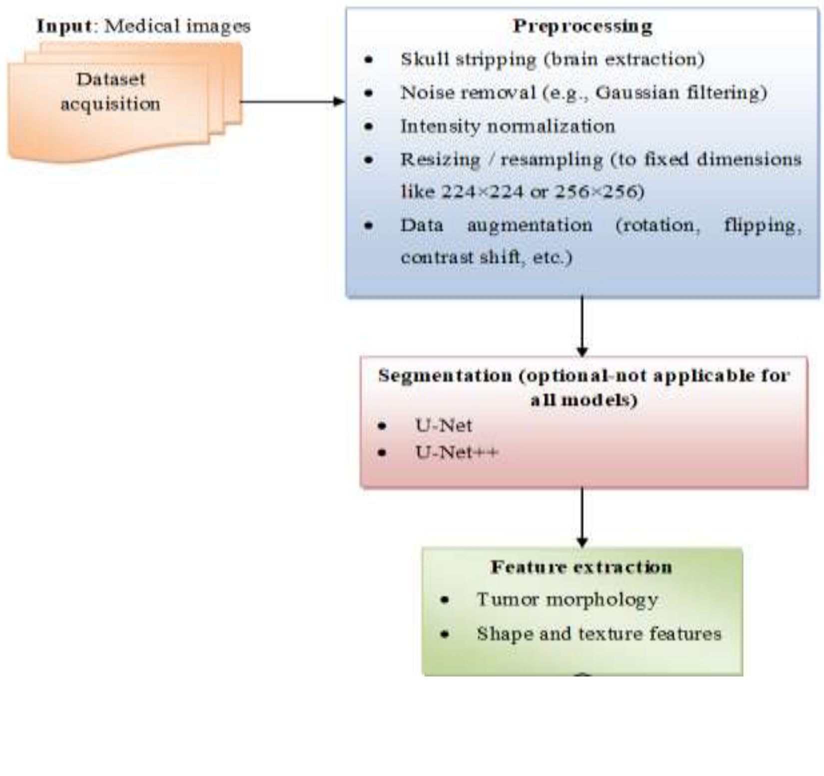


Figure 3: Experimental settings considered in the existing brain tumor diagnosis approaches

5. An End-to-End Deep Learning Framework for Brain Tumor Analysis

The sequential modeling is formulated for brain tumor detection and classification using deep learning involves several key stages, from initial medical imaging to final clinical interpretation. The process pipeline is given in Figure 4.

The sequential model can be carried out by brain tumor detection through classifying outcomes among non-tumorous and tumorous brain regions whereas the brain tumor classification is conducted by classifying the tumors into different categories [31]. Initially, the data acquisition process is conducted by sourcing data from publically available datasets or collected from medical institutions [35]. Secondly, the pre-processing is carried out to prepare the images for deep learning. Thirdly, the tumor segmentation process is performed to localize the tumor region mask especially for finding whether a tumor exists or where it is located. It also analyzes accurate tumor boundaries to isolate the tumor region for better classification results. Feature extraction is another significant process applied for automatic extraction of significant features, maximizing final detection/classification efficiency. The performance analysis is conducted by standard performance evaluation measures such as accuracy, precision, recall, and precision. The final outcomes on tumor detection or classification are beneficial to integrate the model into real-world adoption.



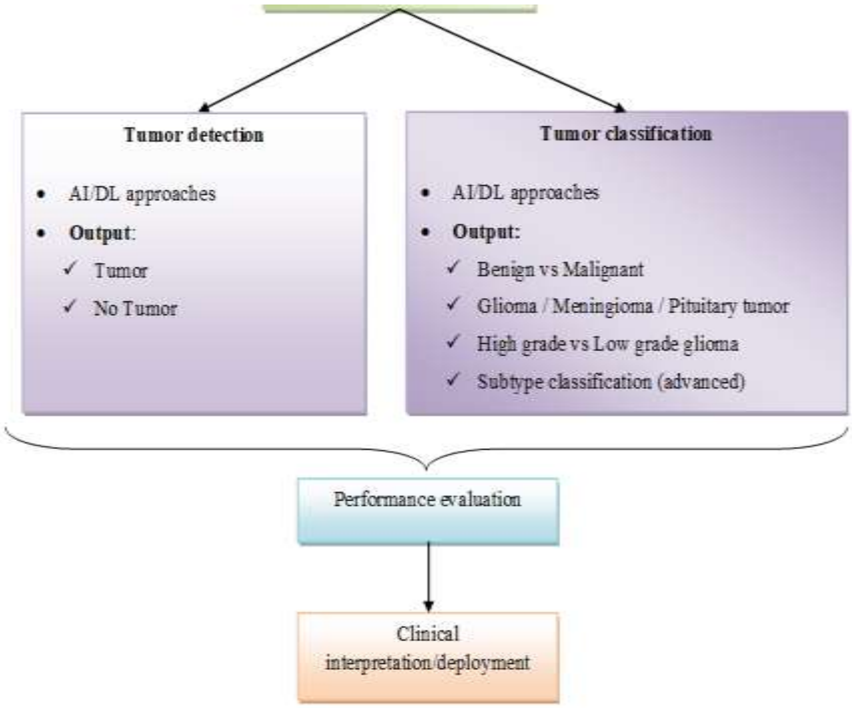


Figure 4: Representation of End-to-End Deep Learning Framework for Brain Tumor Analysis

6. Research Challenges and Future Research Directions

Brain imaging is more useful to visualize functional and structural variations in the brain, resulting from the underlying pathophysiological abnormalities [42]. Various non-invasive medical imaging approaches are useful in detecting and prognosis of neuro-logical diseases [43]. The AI/DL-based approaches are applied to analyze and acquire the outcomes due to the need of labeled and huge-scale datasets for processing [44]. However, unavailability of these multi-modal data for several neurological diseases is another complication in computer-aided design research especially while processing smaller datasets and also observed generalizability problems [47]. An additional problem in this domain is the class imbalance observed in acquired datasets, which also restricts the performance for diverse classes [48]. Moreover, the selection of suitable DL architecture along with suitable hardware resources with the ability of handling huge scale multi-dimensional arrays also increases the challenges especially using multi-modal and multi-class medical imaging data [50]. Additionally, the recent performance problems of the AI-aided computer-driven design approaches limit generalizability and robustness that further hinder the incorporation of such research tools in medical practice [51]. While increasing the accuracy of AI-driven diagnosis models, the complications of the AI system architectures also exponentially increased [54]. It results in reducing the explainability and interpretability. Owing to the utilization of several parameters and layers, DL methodologies have become very large. Despites its promising accuracy in brain tumor diagnosis tasks, their internal processes are challenging to understand, which turns them into “black boxes”. This lack of transparency will result in complexity of trusting these models by medical professionals. While considering the real-world clinical settings, the precise decisions are required as it directly impacts human lives and also it can be disastrous affecting earlier treatments. Therefore, it is crucial to integrate Explainable AI (XAI) solutions for handling these problems and improving trust along with the use of AI in making clear and easier decisions for better interpretation for medical experts. In future, the explainability models must be analyzed to showcase the interpretability and transparency of the brain tumor diagnosis models. The large scale, different and extensive datasets must be analyzed in future for facilitating them to be more generalizable across several neurological conditions. In addition, the technology available to a broad range of clinical experts will use these systems in real-time applications especially towards commercial deployments.

7. CONCLUSION

DL approaches have significantly advanced the field of brain tumor analysis and also consequently improved patient results. To summarize, the recent applications on AI-driven computer-assisted systems especially on brain tumor diagnosis models will have huge benefits. Thus, it observes a demand for further research and design on creating more reliable, comprehensive and diagnostic detection tools for brain tumors. The meticulous analysis of the aspects such as AI techniques for detection and classification methods, performance measures, experimental settings, and dataset details have revealed the significance of the existing frameworks and also guide the future research study on reliable analysis. This review has further offered insights about medical diagnosis models especially on the detection and classification of brain tumors to assist neurologists for earlier treatment.

Funding

The authors received no financial support for the research, authorship, or publication of this work. No external grants or institutional funds were used. All costs were borne by the authors.

Competing Interests
The authors declare that they have no competing interests. There are no financial or non-financial conflicts to disclose. All authors confirm that no conflict has influenced the work.

Data Availability
No new datasets were generated or analyzed during this study. All information used in the research is available within the manuscript.

Ethical Approval
This study did not involve human participants, human data, or human tissue. It also did not involve any animal subjects or experiments.

Consent to Publish
No individual person's data, images, or identifiable information were included. Hence, no consent for publication was required.

Informed Consent Statement
The study does not include human subjects or personal data requiring informed consent. No identifiable information was collected, analyzed, or reported.

Author Contributions
All authors contributed equally to the conceptualization and preparation of the manuscript. No specific role distinctions were applicable for this study.

REFERENCES
[1] Abdusalomov, A.B., Mukhiddinov, M. and Whangbo, T.K., (2023). Brain tumor detection based on deep learning approaches and magnetic resonance imaging. Cancers, 15(16), p.4172.
[2] Adewole, M., Rudie, J.D., Gbadamosi, A.A., Toyobo, O.O., Raymond, C., Zhang, D., Olubukola Omidiji, Akinola, R., Suwaid, M.A., Emegoakor, A., Ojo, N.A., Aguh, K., Kalaiwo, C., Babatunde, G., Ogunleye, A.A., Gbadamosi, Y., Iorpagher, K.P., Calabrese, E., Aboian, M. and Linguraru, M.G. (2023). The Brain Tumor Segmentation (BraTS) Challenge 2023: Glioma Segmentation in Sub-Saharan Africa Patient Population (BraTS-Africa). arXiv (Cornell University). doi:https://doi.org/10.48550/arxiv.2305.19369.
[3] AG, B., Srinivasan, S., P, M., Mathivanan, S.K. and Shah, M.A., (2024). Robust brain tumor classification by fusion of deep learning and channel-wise attention mode approach. BMC Medical Imaging, 24(1), p.147.
[4] Aiya, A.J., Wani, N., Ramani, M., Kumar, A., Pant, S., Kotecha, K., Kulkarni, A. and Al-Danakh, A., (2025). Optimized deep learning for brain tumor detection: a hybrid approach with attention mechanisms and clinical explainability. Scientific Reports, 15(1), p.31386.
[5] Al Hasan, S., Mahim, S.M., Hossen, M.E., Hasan, M.O., Islam, M.K., Livreri, P., Khan, S.U., Alibakhshikenari, M. and Miah, M.S., (2025). DSIT UNet a dual stream iterative transformer based UNet architecture for segmenting brain tumors from FLAIR MRI images. Scientific Reports, 15(1), p.13815.
[6] Al-Ashoor, A., Lilik, F. and Nagy, S., (2025). A Systematic Analysis of Neural Networks, Fuzzy Logic and Genetic Algorithms in Tumor Classification. Applied Sciences, 15(9), p.5186.
[7] Albuquerque, C., Henriques, R. and Castelli, M., (2025). Deep learning-based object detection algorithms in medical imaging: Systematic review. Heliyon, 11(1).
[8] Ali, S.S.A., Memon, K., Yahya, N. and Khan, S., (2025). Deep learning frameworks for MRI-based diagnosis of neurological disorders: A systematic review and meta-analysis. Artificial Intelligence Review, 58(6), p.171.
[9] Alsubai, S., Ojo, S., Nathaniel, T.I., Ayari, M., Baili, J., Almadhor, A. and Al Hejaili, A. (2025). Transfer deep learning and explainable AI framework for brain tumor and Alzheimer's detection across multiple datasets. Frontiers in Medicine, 12. doi:https://doi.org/10.3389/fmed.2025.1618550.
[10] Amjad, U., Raza, A., Fahad, M., Farid, D., Akhunzada, A., Abubakar, M. and Beenish, H., (2025). Context aware machine learning techniques for brain tumor classification and detection–A Review. Heliyon, 11(2).
[11] Azeez, O. and Abdulazeez, A., (2025). Classification of Brain Tumor based on Machine Learning Algorithms: A Review. Journal of Applied Science and Technology Trends, 6(1), pp.01-15.
[12] Baid, U., Satyam, G., Mohan, S., Bilello, M., Calabrese, E., Colak, E., Farahani, K., Kalpathy-Cramer, J., Kitamura, F., Pati, S., Prevedello, L.M., Rudie, J.D., Sako, C., Shinohara, R.T., Bergquist, T., Chai, R., Eddy, J.M., Elliott, J., Reade, W. and Schaffter, T. (2021). The RSNA-ASNR-MICCAI BraTS 2021 Benchmark on Brain Tumor Segmentation and Radiogenomic Classification. doi:https://doi.org/10.48550/arxiv.2107.02314.
[13] Bibi, K., Nawaz, M., Khan, S., Daud, M., Masood, A., Abdelgawad, M.A., Abbasi, S.M.T., Rizwan, Khan, A. and Yuan, W., (2025). Artificial Intelligence–Based Approaches for Brain Tumor Segmentation in MRI: A Review. NMR in Biomedicine, 38(11), p.e70141.
[14] Bibi, N., Courtney, J. and McGuinness, K., (2025). Enhancing brain disease diagnosis with XAI: a review of recent studies. ACM Transactions on Computing for Healthcare, 6(2), pp.1-35.
[15] Bouhafra, S. and El Bahi, H., (2025). Deep learning approaches for brain tumor detection and classification using MRI images (2020 to 2024): a systematic review. Journal of Imaging Informatics in Medicine, 38(3), pp.1403-1433.

[16] Chen, J., Mei, J., Li, X., Lu, Y., Yu, Q., Wei, Q., Luo, X., Xie, Y., Adeli, E., Wang, Y. and Lungren, M.P., (2024). TransUNet: Rethinking the U-Net architecture design for medical image segmentation through the lens of transformers. Medical Image Analysis, 97, p.103280.
[17] Disci, R., Gurcan, F. and Soylu, A., (2025). Advanced brain tumor classification in MR images using transfer learning and pre-trained deep CNN models. Cancers, 17(1), p.121.
[18] Dorfner, F.J., Patel, J.B., Kalpathy-Cramer, J., Gerstner, E.R. and Bridge, C.P., (2025). A review of deep learning for brain tumor analysis in MRI. NPJ Precision Oncology, 9(1), p.2.
[19] Golkarieh, A., Boroujeni, S.R., Kiashemshaki, K., Deldadehasl, M., Aghayarzadeh, H. and Ramezani, A., (2025). Breakthroughs in brain tumor detection: leveraging deep learning and transfer learning for MRI-based classification. Computer and Decision Making: An International Journal, 2, pp.708-722.
[20] Guluwadi, S., (2024). Enhancing brain tumor detection in MRI images through explainable AI using Grad-CAM with Resnet 50. BMC medical imaging, 24(1), pp.1-19.
[21] Gundogan, E., (2025). A novel hybrid deep learning model enhanced with explainable AI for brain tumor multi-classification from MRI images. Applied Sciences, 15(10), p.5412.
[22] Hafeez, Y., Memon, K., Al-Quraishi, M.S., Yahya, N., Elferik, S. and Ali, S.S.A., (2025). Explainable AI in diagnostic radiology for neurological disorders: a systematic review, and what doctors think about it. Diagnostics, 15(2), p.168.
[23] Hosny, K.M. and Mohammed, M.A., (2025). Explainable AI and vision transformers for detection and classification of brain tumor: a comprehensive survey. Artificial Intelligence Review, 58(9), p.259.
[24] Iftikhar, S., Anjum, N., Siddiqui, A.B., Ur Rehman, M. and Ramzan, N., (2025). Explainable CNN for brain tumor detection and classification through XAI based key features identification. Brain Informatics, 12(1), p.10.
[25] Isensee, F., Jäger, P.F., Full, P.M., Vollmuth, P. and Maier-Hein, K.H., (2021, October). nnU-Net for brain tumor segmentation. In International MICCAI Brainlesion Workshop (pp. 118-132). Cham: Springer International Publishing.
[26] Johnson, D.R., Giannini, C., Vaubel, R.A., Morris, J.M., Eckel, L.J., Kaufmann, T.J. and Guerin, J.B. (2022). A Radiologist's Guide to the 2021 WHO Central Nervous System Tumor Classification: Part I—Key Concepts and the Spectrum of Diffuse Gliomas. Radiology, 304(3), pp.494–508. doi:https://doi.org/10.1148/radiol.213063.
[27] Kar, S. and Singh, P.K., (2025). MBTC-Net: Multimodal brain tumor classification from CT and MRI scans using deep neural network with multi-head attention mechanism. Medicine in Novel Technology and Devices, p.100382.
[28] Karagoz, M.A., Nalbantoglu, O.U. and Fox, G.C., (2024). Residual vision transformer (ResViT) based self-supervised learning model for brain tumor classification. arXiv preprint arXiv:2411.12874.
[29] Khan, R., Taj, S., Khan, Z.U., Khan, S.U., Khan, J., Arshad, T. and Ayouni, S., (2025). High-precision brain tumor classification from MRI images using an advanced hybrid deep learning method with minimal radiation exposure. Journal of Radiation Research and Applied Sciences, 18(4), p.101858.
[30] Khandaker, M.A.A., Raha, Z.S., Iqbal, S.B., Mridha, M.F. and Shin, J., (2024), December. From Images to Insights: Transforming Brain Cancer Diagnosis with Explainable AI. In 2024 27th International Conference on Computer and Information Technology (ICCIT) (pp. 891-896).
[31] Liu, Z., Tong, L., Chen, L., Jiang, Z., Zhou, F., Zhang, Q., Zhang, X., Jin, Y. and Zhou, H., (2023). Deep learning based brain tumor segmentation: a survey. Complex & intelligent systems, 9(1), pp.1001-1026.
[32] Lv, C., Shu, X.J., Liang, Q., Qiu, J., Xiong, Z.C., bo Ye, J., bo Li, S., Liu, C.Q., Niu, J.Z., Chen, S.B. and Rao, H., (2025). BrainTumNet: multi-task deep learning framework for brain tumor segmentation and classification using adaptive masked transformers. Frontiers in Oncology, 15, p.1585891.
[33] Lyu, Y. and Tian, X., (2025). MWG-UNet++: Hybrid transformer U-Net model for brain tumor segmentation in MRI scans. Bioengineering, 12(2), p.140.
[34] Mastoi, Q.U.A., Latif, S., Brohi, S., Ahmad, J., Alqhatani, A., Alshehri, M.S., Al Mazroa, A. and Ullah, R., (2025). Explainable AI in medical imaging: an interpretable and collaborative federated learning model for brain tumor classification. Frontiers in Oncology, 15, p.1535478.
[35] Mittal, P., (2025). From black box AI to XAI in neuro-oncology: a survey on MRI-based tumor detection. Discover Artificial Intelligence, 5(1), pp.1-21.
[36] Osei, I., Appiah-Kubi, B., Frimpong, B.K., Hayfron-Acquah, J.B., Owusu-Agyemang, K., Ofori-Addo, S., Turkson, R.E. and Mawuli, C.B., (2023), December. Multimodal Brain Tumor Segmentation Using Transformer and UNET. In 2023 20th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP) (pp. 1-6). IEEE.
[37] Pemberton, H.G., Wu, J., Kommers, I., Müller, D.M.J., Hu, Y., Goodkin, O., Vos, S.B., Bisdas, S., Robe, P.A., Ardon, H., Bello, L., Rossi, M., Sciortino, T., Nibali, M.C., Berger, M.S., Hervey-Jumper, S.L., Bouwknegt, W., Van, Furtner, J. and Han, S.J. (2023). Multi-class glioma segmentation on real-world data with missing MRI sequences: comparison of three deep learning algorithms. Scientific Reports, 13(1). doi:https://doi.org/10.1038/s41598-023-44794-0.
[38] Pourmahboubi, A., Arsalani Saeed, N. and Tabrizchi, H., (2025). A brain tumor segmentation enhancement in MRI images using U-Net and transfer learning. BMC Medical Imaging, 25(1), p.307.
[39] Rahman, A., Hayat, M., Iqbal, N., Alarfaj, F.K., Alkhalaf, S. and Alturise, F., (2025). Enhanced MRI brain tumor detection using deep learning in conjunction with explainable AI SHAP based diverse and multi feature analysis. Scientific Reports, 15(1), p.29411.
[40] Rasheed, M., Iqbal, S., Jaffar, A. and Akram, S., (2025). Advanced deep learning-based brain tumor classification using a novel customized CNN and optimized residual network. Plos one, 20(10), p.e0334430.

[41] Rasheed, M., Jaffar, M.A., Akram, A., Rashid, J., Alshalali, T.A.N., Irshad, A. and Sarwar, N., (2025). Improved brain tumor classification through DenseNet121 based transfer learning. Discover Oncology, 16(1), p.1645.
[42] Rasool, N. and Bhat, J.I., (2025). Brain tumour detection using machine and deep learning: a systematic review. Multimedia tools and applications, 84(13), pp.11551-11604.
[43] Raza, A., Guzzo, A., Ianni, M., Lappano, R., Zanolini, A., Maggiolini, M. and Fortino, G., (2025). Federated Learning in radiomics: A comprehensive meta-survey on medical image analysis. Computer Methods and Programs in Biomedicine, p.108768.
[44] Saifullah, S., Dreżewski, R., Yudhana, A., Caesarendra, W. and Huda, N., (2025). Bio-Inspired Metaheuristics in Deep Learning for Brain Tumor Segmentation: A Decade of Advances and Future Directions. Information, 16(6), p.456.
[45] Saranya, M. and Praveena, R., (2025). Accurate and real-time brain tumour detection and classification using optimized YOLOv5 architecture. Scientific Reports, 15(1), p.25286.
[46] Saranya, M. and Praveena, R., (2025). Accurate and real-time brain tumour detection and classification using optimized YOLOv5 architecture. Scientific Reports, 15(1), p.25286.
[47] Sheikh, A.M., Islam, M.R., Habaebi, M.H., Zabidi, S.A., Rahman, A. and Kabbani, A. (2025). A survey on edge computing (EC) security challenges: Classification, threats, and mitigation strategies. Future Internet, [online] 17(4), pp.175–175. doi:https://doi.org/10.3390/fi17040175.
[48] Shoushtari, F.K., Elahi, R., Valizadeh, G., Moodi, F., Salari, H.M. and Rad, H.S., (2025). Current trends in glioma tumor segmentation: A survey of deep learning modules. Physica Medica, 135, p.104988.
[49] Shuvo, S.S., Refat, S.R., Preotee, F.F. and Muhammad, T., (2024, October). Advanced CNN and Explainable AI Based Architecture for Interpretable Brain MRI Analysis. In Proceedings of the 3rd International Conference on Computing Advancements (pp. 319-326).
[50] Supriyadi, M.R., Samah, A.B.A., Muliadi, J., Awang, R.A.R., Ismail, N.H., Majid, H.A., Othman, M.S.B. and Hashim, S.Z.B.M., (2025). A systematic literature review: exploring the challenges of ensemble model for medical imaging. BMC Medical Imaging, 25(1), p.128.
[51] The Cancer Imaging Archive (2024). RSNA-ASNR-MICCAI-BraTS-2021. [online] The Cancer Imaging Archive (TCIA). Available at: https://www.cancerimagingarchive.net/analysis-result/rsna-asnr-miccai-brats-2021/.
[52] Ullah, M.S., Khan, M.A., Masood, A., Mzoughi, O., Saidani, O. and Alturki, N., (2024). Brain tumor classification from MRI scans: a framework of hybrid deep learning model with Bayesian optimization and quantum theory-based marine predator algorithm. Frontiers in Oncology, 14, p.1335740.
[53] Vamsidhar, D., Desai, P., Joshi, S., Kolhar, S., Deshpande, N. and Gite, S. (2025). Hybrid model integration with explainable AI for brain tumor diagnosis: a unified approach to MRI analysis and prediction. Scientific Reports, 15(1). doi:https://doi.org/10.1038/s41598-025-06455-2.
[54] Wang, P., Yang, Q., He, Z. and Yuan, Y., (2023). Vision transformers in multi-modal brain tumor MRI segmentation: A review. Meta-Radiology, 1(1), p.100004.
[55] Wong, Y., Su, E.L.M., Yeong, C.F., Holderbaum, W. and Yang, C., (2025). Brain tumor classification using MRI images and deep learning techniques. PloS one, 20(5), p.e0322624.
[56] Zahoor, M.M., Khan, S.H., Alahmadi, T.J., Alsahfi, T., Mazroa, A.S.A., Sakr, H.A., Alqahtani, S., Albanyan, A. and Alshemaimri, B.K., (2024). Brain tumor MRI classification using a novel deep residual and regional CNN. Biomedicines, 12(7), p.1395.
[57] Zahoor, M.M., Qureshi, S.A., Bibi, S., Khan, S.H., Khan, A., Ghafoor, U. and Bhutta, M.R., (2022). A new deep hybrid boosted and ensemble learning-based brain tumor analysis using MRI. Sensors, 22(7), p.2726.
[58] Zeineldin, R.A., Karar, M.E., Burgert, O. and Mathis-Ullrich, F., (2022, September). Multimodal CNN networks for brain tumor segmentation in MRI: a BraTS 2022 challenge solution. In International MICCAI Brainlesion Workshop (pp. 127-137). Cham: Springer Nature Switzerland.
[59] Zhang, M., Sun, Q., Han, Y., Zhang, M., Wang, W. and Zhang, J., (2025). Generative adversarial DacFormer network for MRI brain tumor segmentation. Scientific Reports, 15(1), p.17840.
[60] Zongren, L., Silamu, W., Shurui, F. and Guanghui, Y., (2023). Focal cross transformer: multi-view brain tumor segmentation model based on cross window and focal self-attention. Frontiers in Neuroscience, 17, p.1192867.