



Advancements in Brain Tumour Analysis: A Review of Machine Learning, Deep Learning, Image Processing, and Explainable AI Techniques

S. Venu Gopal¹ · C. H. Kavitha²

Received: 6 March 2025 / Accepted: 17 April 2025 / Published online: 5 May 2025
© The Author(s), under exclusive licence to Springer Nature Switzerland AG 2025

Abstract

Segmenting and detecting Brain Tumours (BTs) stands a substantial task in medical image examination. A tumour arises from the rapid and uncontrolled proliferation of cells in the brain. The primary objective of brain tumour separation is to accurately outline the regions affected by the tumour. Nowadays, Deep Learning (DL) approaches have revealed notable efficacy in addressing diverse mainframe vision challenges with image sorting, target recognition, and semantic segmentation. Numerous deep learning techniques have been employed for BT segmentation and categorization, demonstrating promising outcomes and integration of explainable AIs makes an impact on brain tumour analysis. Leveraging the advancements in modern technologies, this survey presents a complete examination of recently established atlas and statistical-based deep learning methods for BT separation and categorization. The survey encompasses an analysis of over 105 standard research papers, exploring into various technical aspects like different segmentation techniques, different classification techniques, dataset contribution, and the performances. Additionally, the survey offers insightful discussions on possible solutions for future expansion in this field.

Keywords Atlas-based techniques · Statistical-based techniques · Brain tumour classification · Brain tumour segmentation · Magnetic resonance images · Explainable AIs

✉ S. Venu Gopal
venuace76@gmail.com

C. H. Kavitha
kavithachaduvula12@gmail.com

¹ Department of Computer Science and Engineering, JNTUK, Kakinada, Andhra Pradesh 533003, India

² Department of Information Technology, Seshadri Rao Gudlavalluru Engineering College, Gudlavalluru, Andhra Pradesh 521356, India

1 Introduction

Brain tumours (BTs) are a major global health problem because of their multifaceted nature, broad range of types, and mixed malignancy grades. Conventional diagnostic techniques have frequently been challenged by the complex borders and heterogeneous presentations of tumours, leading to the investigation of newer techniques like DL to improve diagnostic accuracy and efficiency [1–3]. Precise early identification of malignant BTs is essential to enhance patient survival rates [4, 5], and several methods have been put forward to accurately segment and classify these tumours. Utilizing advanced medical imaging modalities and complementary technologies, BT images are obtained to augment diagnostic systems in clinics [6]. Clinically, doctors look for solutions not only being technically sound but economical too, with a focus on quick and true detection. Increasingly, classifying BTs according to established clinical procedures so that there is complete understanding and proper planning of treatment is also given priority [7]. Fig. 1 shows the worldwide figures of people diagnosed with brain tumours in 2020 [8]. This gives a general overview of the distribution and prevalence of brain tumour cases by region around the world during that year.

In this context, DL techniques have become a revolutionary technique in BT image analysis. Being a branch of machine learning (ML), DL shows outstanding ability to learn hierarchical representations of data from raw and complicated data sets [9–12], providing dramatic improvements in segmentation and classification tasks. Additionally segmentation is a difficult task because of various inherent factors like high variability in tumour shape, size, and location between patients; low contrast between tumour and tissues; existence of noise and imaging artifacts; and class imbalance between tumour and non-tumour regions. These difficulties are further compounded by the limited number of annotated datasets, and hence, accurate and robust segmentation becomes challenging in clinical practice.

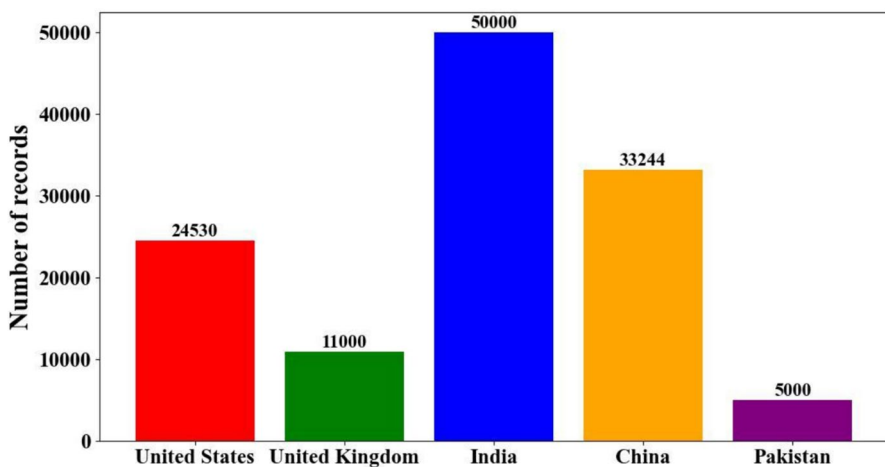


Fig. 1 Global brain tumour statistics for 2020

In contrast to conventional image processing methods, which tend to fail when faced with variability of tumours in shape, size, and texture, DL models learn features that reflect the inherent heterogeneity of BTs adaptively [13–15]. This results in more accurate tumour boundary delineation and enables strong classification according to tumour type, grade, or other pertinent factors [16]. The overarching aims of using DL for brain tumour analysis are (1) obtaining precise segmentation to enable improved tumour boundary detection and treatment planning; (2) improving classification performance to achieve subtype or grade identification; and (3) applying automation to facilitate clinical workflows with increased consistency and lower manual intervention [17–20]. Fig. 2 illustrates the taxonomy of ML and DL methods for brain tumour diagnoses.

Given the critical role of DL in revolutionizing BT diagnosis, this review aims to systematically examine and analyse recent advances in ML and DL approaches for BT segmentation and categorization. Specifically, the review highlights the evolution of traditional ML approaches, the rise of advanced DL models, and the growing interest in hybrid and explainable AI(XAI) frameworks tailored to brain tumour analysis. The key objective of this survey is to explain the intricate mechanisms employed by these DL systems.

This review presents a thorough analysis of over 105 recent studies published between 2020 and 2024, offering a comprehensive and up-to-date examination

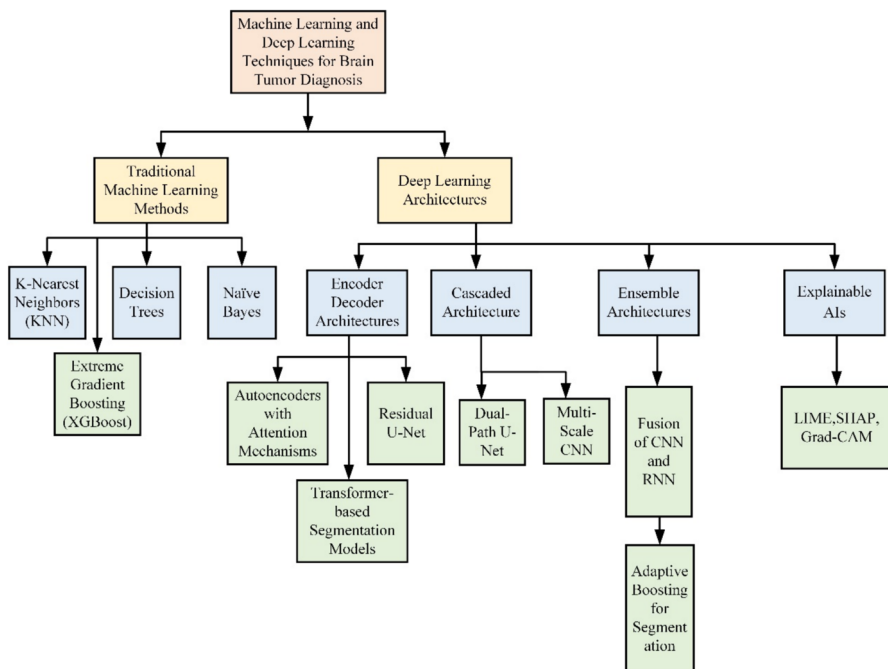


Fig. 2 Taxonomy of ML and DL techniques for brain tumour diagnoses

of atlas-based, statistical, ML, DL, hybrid, and XAI approaches used for BT segmentation and analysis.

Unlike previous reviews that typically focus on isolated methodologies, this work provides an integrated perspective by synthesizing conventional image processing techniques with ML, DL, and XAI approaches. This holistic view enhances the understanding of how these techniques complement one another in brain tumour detection and diagnosis.

The review distinguishes itself by critically comparing a wide range of methodologies, including underexplored techniques, and offering a balanced assessment of their relative advantages and limitations. This depth of analysis delivers novel insights not commonly addressed in prior literature.

Furthermore, this survey highlights real-world clinical implications and proposes clear future research directions, addressing current deployment challenges. This forward-looking approach not only consolidates existing knowledge but also serves as a roadmap for ongoing innovation in brain tumour analysis.

Survey organization The introduction in Sect. 1 is followed by the scope of the survey and a chronological evaluation of existing research in Sect. 2. Section 3 provides a comprehensive literature review, covering ML, DL, hybrid approaches, and XAI. This section categorizes the reviewed methods into atlas-based and statistical-based DL techniques, and also highlights key research gaps in these foundational approaches. Section 4 discusses the experimental results and major contributions of the survey. Section 5 discusses the emerging challenges and outlines potential future scope, while Sect. 6 concludes the survey with final remarks.

2 Evolution Timeline of Brain Tumour Segmentation

Brain tumour segmentation developed from traditional image processing techniques like thresholding (2011–2013) and watershed segmentation to feature learning on machine learning methods like K-Means Clustering (2014–2016) and Random Forest. The revolution with DL came in 2017–2019, bringing CNN models like ResNet and U-Net, when hand-crafted feature engineering disappeared. Complex models with attention, transformers, and generative networks (2020–2022) have further enhanced segmentation accuracy. Latest trends (2023–2025) explore quantum-assisted DL, federated learning for privacy, and neuromyotonic AI for improving the precision and interpretability of tumour segmentation in medical analysis. Fig. 3 depicts the evolution of brain tumour segmentation.

2.1 Scope of Survey

In this survey, compiled research findings from over numerous research works, examining prominent journals like IEEE, Springer, Elsevier, MDPI, and Hindawi, aim to capture the latest outcomes in border medical imaging research. The main

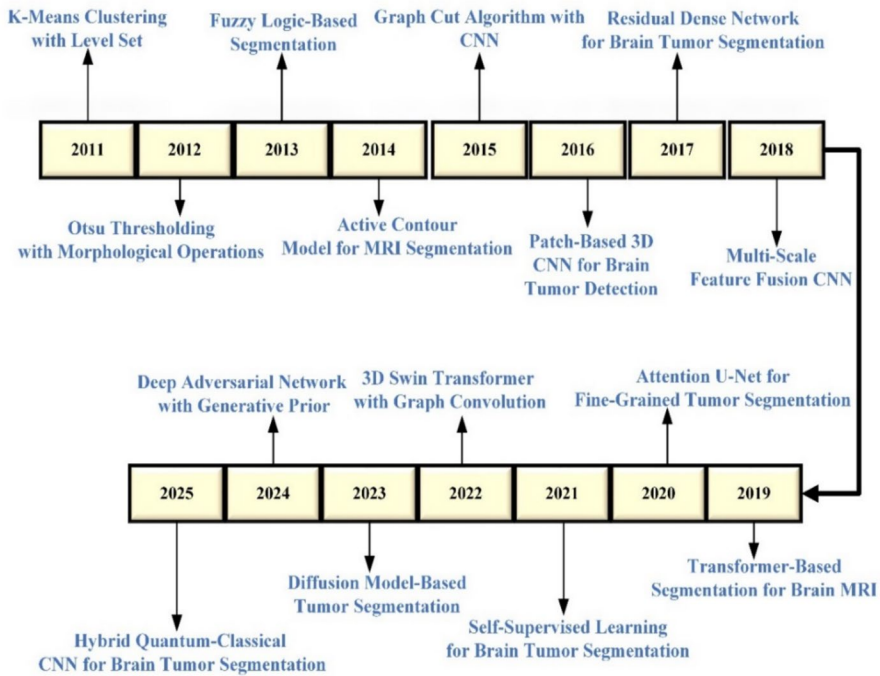


Fig. 3 Evolution of brain tumour segmentation

objective of this survey is to offer a complete technical evaluation of DL-based BT segmentation and classification methods, categorizing them according to atlas-based and statistical-based features and strategy comparisons. The main goal is to explore the impact of diverse architectures on the segmentation and classification performance of deep neural systems, while also examining how various learning strategies are enhanced to address key challenges in brain tumor segmentation and detection. The attention extends complex considerations, with efficient construction strategy, disparity segmentation, and multi-modality processing.

2.2 Chronological Evaluation

The chronological evaluation of BT recognition approaches based on prevailing methods is depicted in Fig. 4, organized corresponding to publication ages. BT recognition has been a major focus of research, and this survey has compiled numerous research works spanning from 2020 to 2025.

The percentage distribution of contributions in 2020 is noted as 28.5%. In 2021 it is noted as 16%. In 2022 and 2023, 24.5% in each year contributed, and in 2024 it is noted as 6.4% of research works have been included in this survey. The contributions from 2020 establish 9.2% of the evaluation. In the years 2021 to 2024, 21.7% of contributions are analysed in this survey.

Fig. 4 A year-wise contribution of BT segmentation and classification

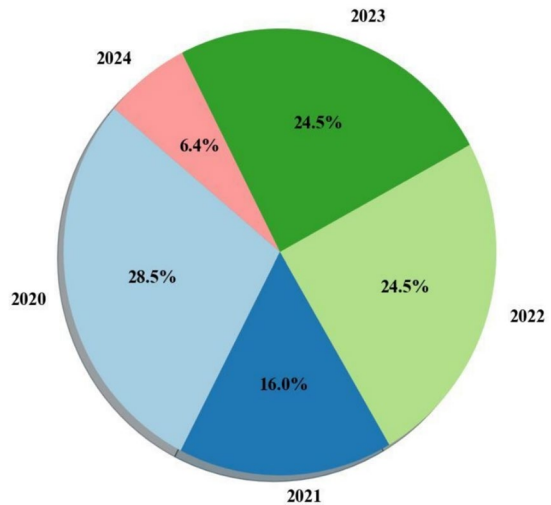


Fig. 5 outlines the three stages of the inclusion-exclusion criteria based on the Prisma process: (1) the total number of research papers considered as input (I/P), (2) the filtration process applied, and (3) the filtered research papers as output (O/P).

The stages are as follows:

Initially, 347 research papers are considered. After excluding those with irrelevant titles, 194 articles are selected for further review.

From these 194 papers, 27 are excluded based on irrelevant abstracts and conclusions.

Of the remaining 167 articles, 125 are selected, excluding those with inappropriate content.

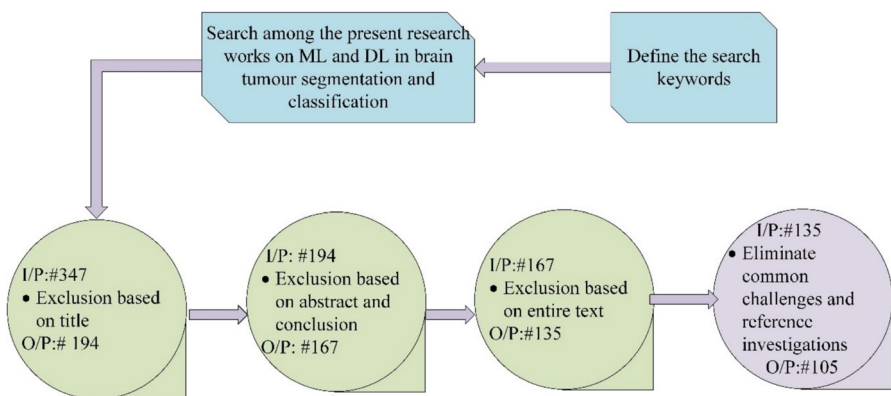


Fig. 5 Inclusion and exclusion criteria based on the Prisma process

Finally, after addressing common challenges and reviewing references, 105 articles are chosen for the final review process.

2.3 Review Questions

- o **RQ1:** How do traditional ML techniques compare to DL approaches in terms of effectiveness for detection and classification BTs from medical imaging data?
- o **RQ2:** What are the key image processing techniques that enhance feature extraction and segmentation accuracy for BT analysis using ML and DL techniques?
- o **RQ3:** How does the integration of DL and innovative image processing techniques improve the early diagnosis and prognosis of BTs, particularly in terms of accuracy, efficiency, and clinical usability?

3 Literature Review on Various Contributions of Brain Tumour Segmentation and Classification Using Machine Learning and Deep Learning Algorithms

This section reviews key contributions in BT segmentation and categorization via ML and DL algorithms. Early ML methods depend on handcrafted features, while recent DL models like CNNs and U-Nets learn directly from medical images, offering improved accuracy and robustness. Hybrid and ensemble models have further enhanced performance. The review summarizes major techniques, datasets, and results to highlight current progress and research directions in automated brain tumour analysis. Table 1 depicts the related comparison of ML and DL techniques for BT analysis.

3.1 Comprehensive Review of ML Approaches in Brain Tumour Segmentation and Classification

ML approaches have long served as foundational tools for brain tumour analysis, especially in segmentation and classification tasks. These approaches depend on extracting informative features from MRI scans and feeding them into classifiers for decision-making. The increasing volume of medical imaging data has led to a growing need for scalable and reliable algorithms, prompting early studies to assess the functionality of diverse ML frameworks in BT diagnosis. Several works, including [21, 22, 25, 30], demonstrate the applicability of supervised ML algorithms, yet underline significant dependencies on feature design, parameter tuning, and human intervention.

3.1.1 Feature Extraction and Selection Techniques

Feature engineering is pivotal in ML-based tumour classification. Techniques such as texture descriptors, intensity-based histograms, (e.g., GLCM, LBP), shape analysis, and statistical measures are commonly used. [26] emphasized

Table 1 Comparison of ML and DL techniques for BT analysis

Techniques	Key algorithms	Feature extraction	Performance (accuracy %)	Advantages	Limitations
Traditional ML	SVM, Random Forest, k-NN, Decision Tree	Manual (texture, shape, intensity)	75–85%	Requires less computational power, interpretable models	Relies on handcrafted features, lower adaptability
Hybrid ML-DL	CNN + SVM, PCA + k-NN, RF + Deep Features	Partial (deep feature extraction)	85–90%	Combines strengths of both ML and DL, improved accuracy	Increased complexity, requires feature engineering
Deep learning	CNN (AlexNet, VGG16, ResNet), U-Net, Transformer-based models	Automatic (hierarchical feature learning)	90–98%	Higher accuracy, automated feature learning, robust to variations	Requires large datasets, computationally expensive

multi-level fusion of handcrafted features, while [24] employed correlation-based selection and genetic algorithms to isolate discriminative attributes. These strategies aim to enhance model interpretability and accuracy by eliminating redundant or noisy features. However, their effectiveness heavily depends on domain expertise and dataset characteristics, making scalability a concern in clinical settings.

3.1.2 Classical ML Algorithms

Various classical algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Decision Trees (DT), and Naïve Bayes have been widely employed. [30] directed a relative assessment of these approaches, finding SVM and RF to offer balanced performance across sensitivity and specificity. [25] reinforced these observations using real-time clinical MRI datasets. Meanwhile, [27] suggested a hybrid system integrating CNN-based features with ML classifiers, revealing that leveraging deep features significantly enhance classification accuracy, despite using classical models downstream.

3.1.3 Ensemble and Meta-Learning Strategies

To overcome individual model limitations, ensemble learning techniques like Bagging, Boosting (e.g., AdaBoost, XGBoost), and stacking have been introduced to increase robustness and reduce overfitting. [29, 31] incorporated ensemble strategies with RadImageNet-pretrained CNNs and ML classifiers to produce consistent results across multiple tumour classes. Similarly, [28] proposed hybrid frameworks integrating optimized SVMs with deep networks for multiclass classification, achieving improved generalization. These methods collectively demonstrate the potential of ensemble strategies, especially when leveraging both feature-level and decision-level fusion techniques. Table 2 depicts the challenges addressed by ML.

3.1.4 Limitations and Challenges of ML-Based Approaches

Despite their early success, traditional ML methods exhibit several critical limitations. First, their dependency on handcrafted features makes them less adaptable to heterogeneous and high-dimensional medical data. Second, they lack end-to-end learning capability, often requiring separate stages for preprocessing, feature extraction, and categorization, as noted by [2] and [1]. Furthermore, ML models struggle with extracting spatial and contextual relationships in MRIs, which are essential for accurate segmentation. Overfitting due to limited annotated data, scalability challenges, and sub-optimal performance in multiclass scenarios are persistent barriers. These constraints have collectively motivated a paradigm shift toward deep learning-based methods, which offer automated feature learning and better scalability for complex tumour classification tasks.

Table 2 Challenges addressed by machine learning

Reference	Challenge	How machine learning addresses it	Critical aspects
[21]	Feature selection complexity	Uses automated feature extraction methods like PCA and LDA	PCA captures variance but is linear and unsupervised; LDA considers class separation, making it more effective for classification tasks in brain tumour analysis
[22]	High dimensionality of MRI data	Dimensionality reduction technique such as t-SNE and PCA	While PCA is efficient for linear reductions, t-SNE provides better visualization in non-linear space but lacks scalability for large datasets
[23]	Very minimal availability of labelled data	Uses supervised learning and synthetic data generation	Supervised methods require labels and perform well when sufficient data exists, whereas synthetic generation like GANs introduces variability but affect practicality
[24]	Noise and artifacts in MRI images	Implements filtering techniques like wavelet transform and Gaussian filters	Gaussian filtering smoothens but blurs edges; wavelet transforms preserve local features better, making them more suitable for structural preservation in tumour regions
[25]	Class imbalance in tumour vs. non-tumour regions	Applies SMOTE and cost-sensitive learning approaches	SMOTE balances data by oversampling minority classes but introduces noise; cost-sensitive learning adapts models to penalize misclassification, improving reliability

3.2 Comprehensive Review of Traditional DL Approaches in Brain Tumour Segmentation and Classification

This section provides a comprehensive review of traditional DL approaches for BT segmentation and categorization, primarily focusing on CNNs, RNNs, and Transfer Learning (TL) approaches. It highlights how these models utilize spatial hierarchies and pretrained architectures to process MRI data and improve tumour detection. Performance across benchmark datasets is discussed, along with the limitations of traditional methods concerning overfitting, generalization, and interpretability.

3.2.1 CNN-Based Segmentation Architectures

CNNs have been essential in BT investigation due to their strong capability to absorb spatial hierarchies from MRI scans. Early works like [3] and [32] laid foundational models by integrating CNNs with optimization techniques to improve classification accuracy. Subsequently, [33–36] suggested a CNN-based segmentation framework that utilized dual encoder-decoders and multi-level feature extraction for improved delineation of tumour regions. Further, [41] introduced a fully automated CNN-based diagnostic system that excelled in tumour classification using T1-weighted MRI, emphasizing end-to-end feature learning. [40] advanced the design with an ensemble of ResNet and Broad Learning System (RBEBT) to boost classification accuracy, and [45] demonstrated that combining CNN with SVM classifiers significantly increases interpretability and precision. Similarly, [38] combined multiple CNN features with k-means clustering and PCA to enhance class discrimination and reduce dimensionality, reinforcing the flexibility of CNN pipelines.

3.2.2 RNN and LSTM-Based Temporal Models

While RNNs and LSTMs are more prominent in temporal data applications, their role in brain tumour analysis has been to explore sequential patterns across slices or time-point scans. Although not the main focus in many reviewed works, [43] hinted at using LSTM layers to process 3D volume data slice-by-slice for classification. In scenarios where tumour growth progression needs to be monitored, LSTM networks are positioned to model time-dependent changes, although such applications remain underutilized in the existing studies.

3.2.3 Transfer Learning and Pretrained Models

TL, using models such as VGGNet, ResNet, or Inception trained on ImageNet, has become essential for overcoming data scarcity in medical imaging. [39] proposed a two-stage CNN ensemble framework where pretrained CNNs were fine-tuned on tumour data, enhancing generalizability. Likewise, [40] and [38]

adopted TL strategies, showing significant performance gains with fewer training epochs. [47] emphasized that pretrained features from deeper architectures help capture high-level semantic representations necessary for subtle tumour variation detection.

3.2.4 Performance Evaluation on Benchmark Datasets

Many studies evaluated their models on benchmark datasets like BraTS2015, BraTS2017, or institutional MRI databases. [35] and [48] used BraTS datasets to benchmark their segmentation accuracy using Dice Coefficient (DC), Jaccard Index (IoU), and Hausdorff Distance. [37] reported enhanced results on local datasets using LSSVMs and texture fusion techniques. [42] also emphasized multi-class performance evaluation on BraTS through improved thresholding techniques and optimized CNN architectures. Additionally, [32] integrated optimization techniques like PSO with CNNs, and validated their model's using metrics like sensitivity, specificity, and precision. Table 3 depicts the challenges addressed by deep learning.

Tables 4 and 5 depict the segmentation outcomes of the DL models in the BRATS and Kaggle datasets.

3.2.5 Limitations of Traditional DL Models

Despite strong performance, conventional DL approaches suffer from several limitations. Overfitting due to limited medical data is a consistent challenge, as discussed by [46] and [47]. CNNs often fail to generalize across institutions due to variations in scanning protocols, intensity normalization, and patient demography. Moreover, traditional models lack explainability, making clinical integration difficult, as pointed out by [51] and [54]. Furthermore, these models are data-hungry and often require extensive preprocessing and annotation, limiting scalability in real-world clinical settings, as observed in [52] and [56–65].

3.3 Comprehensive Review of Hybrid DL Approaches in Brain Tumour Segmentation and Classification

This section explores hybrid deep learning strategies that enhance traditional models by integrating attention mechanisms, optimization algorithms, and multimodal learning. These approaches aim to improve context modeling, robustness, and accuracy in brain tumour analysis. The section reviews CNN-transformer hybrids, attention-guided frameworks, and the fusion of deep learning with metaheuristics for better segmentation and classification performance.

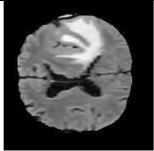
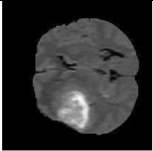
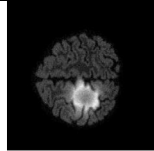
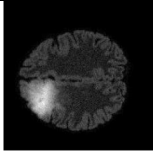
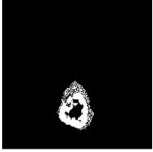
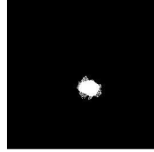
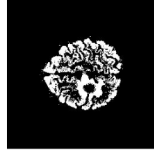
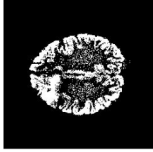
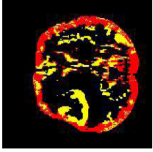
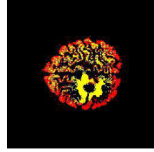
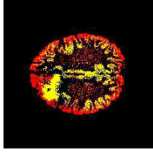
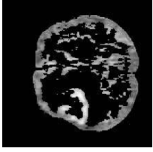
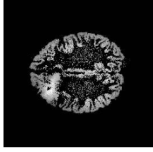
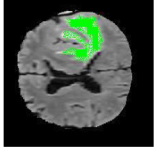
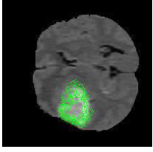
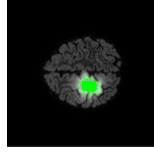
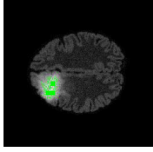
3.3.1 CNN-Transformer Hybrid Architectures

With the rise of Vision Transformers (ViTs), combining CNNs with Transformers has gained attention for enhancing global context understanding in medical images. While not all references explicitly apply ViTs, concepts of integrating contextual

Table 3 Challenges addressed by deep learning

Refs	Challenge	How DL addresses it	Critical aspects
[43]	Variability in tumour shapes and sizes	Uses CNNs and Transformers to capture multi-scale tumour variations	CNNs excel in local feature extraction but struggle with global context; transformers complement this by modeling long-range dependencies, offering better shape generalization
[45]	Minimum contrast between tumour and normal tissue	Uses attention mechanisms and contrast enhancement techniques	Attention mechanisms selectively enhance relevant features, improving contrast detection, while enhancement techniques increase noise if not tuned properly
[46]	Limited annotated data for training	Implements self-supervised learning and data augmentation	Data augmentation is effective but limited in novelty; self-supervised methods offer better generalization but are still evolving and require careful pretext task design
[53]	High computational costs	Uses optimized architectures like MobileNet and quantization	MobileNet provides lightweight inference but sacrifice accuracy; quantization reduces memory footprint, though it affects model precision if not calibrated well
[55]	Class imbalance in tumour vs. background	Applies loss functions like focal loss and dice coefficient	Focal loss emphasizes hard examples but under-train easier ones; dice coefficient handles imbalance well in segmentation but is sensitive to boundary misclassifications

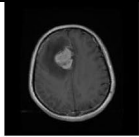
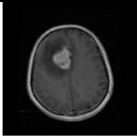
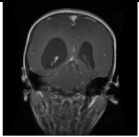
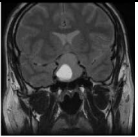
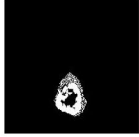
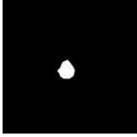
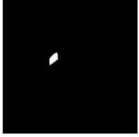
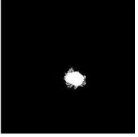
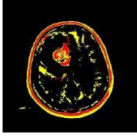
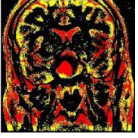
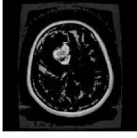
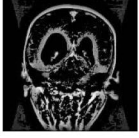
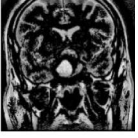
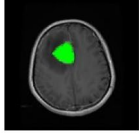
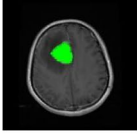
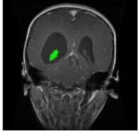
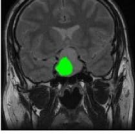
Table 4 Segmentation results of the proposed method in the BRATS datasets

Steps	Output of BRATS dataset			
	Image1	Image2	Image3	Image4
Input Image				
Ground Truth Image				
Binary image				
Cluster image				
Pixel portion				
Segmented output				

modeling are evident. For instance, [48] embedded attention mechanisms that mimic transformer-like contextual encoding in their GammaNet, achieving intensity-invariant segmentation. [37] introduced an ensemble of CNNs that implicitly modeled inter-patch relationships, a foundational trait of Transformer mechanisms. These hybrid designs seek to combine the spatial localization power of CNNs with the long-range dependency modeling of Transformers, although direct CNN-Transformer architectures remain a developing frontier in the reviewed works. Table 6 depicts the integration of DL and advanced image processing methods for BT Analysis.

Fig. 6 Depicts the analysis of dataset usage in brain tumour analysis research.

Table 5 Segmentation results of the proposed method on the Kaggle dataset

Steps	Output of Kaggle dataset			
	Image1	Image2	Image3	Image4
Input Image				
Ground Truth Image				
Binary image				
Cluster image				
Pixel portion				
Segmented output				

3.3.2 Integration of Attention Mechanisms and Graph-based Models

Attention mechanisms have been embedded to enhance focus on salient tumour regions. [38] used a region-aware attention module to dynamically refine features across different modalities. [52] introduced a hybrid model using Region of Interest (ROI)-based attention combined with DL to isolate tumour boundaries more precisely. Though graph-based models were not central in many studies, works like [49] applied fuzzy rule-based segmentation and [42] used watershed-based thresholding, which reflect early forms of spatial relational modeling that align with graph-theoretic approaches.

Table 6 Integration of DL and advanced image processing methods for BT analysis

Deep learning model	Image processing technique	Key functionality	Performance enhancement	Clinical implications	Limitations and considerations
CNN (AlexNet, VGG16, ResNet)	Histogram equalization, contrast enhancement	Improves image clarity and feature detection	Enhances early tumour classification accuracy by 10–15%	Helps in rapid and automated initial screening	Limited in handling spatial context; underperform on complex or low-contrast cases
U-Net, Mask R-CNN	Edge detection, morphological operations	Accurate tumour segmentation and boundary refinement	Reduces segmentation errors by 20%	Aids neurosurgeons in precise surgical planning	Requires large labelled datasets; struggles with generalization across imaging protocols
Hybrid CNN + TL	Wavelet transform; Fourier transform	Extracts multi-resolution features for tumour classification	Increases model robustness in noisy images	Enables better adaptation to diverse MRI datasets	Pre-trained models introduce bias; domain mismatch affects performance
GANs (Generative Adversarial Networks)	Data augmentation, super-resolution	Generates synthetic MRI data to overcome dataset limitations	Improves model generalization, especially for rare tumour	Addresses data scarcity issues in DL training	Risk of generating unrealistic images; training instability is common
Attention-based CNNs	Feature map optimization, ROI extraction	Focuses on critical tumour regions while reducing background noise	Enhances sensitivity in small and irregular tumours	Reduces false positives in early-stage tumour detection	Computationally intensive; overfit to irrelevant regions without proper regularization
Radiomics-based DL	Texture analysis, shape and intensity feature extraction	Quantitative imaging biomarker extraction for prognosis	Provides explainable AI-based insights for oncologists	Assists in personalized treatment and survival prediction	Requires standardization of imaging protocols and reproducibility across centers
Multimodal DL (MRI + CT + PET)	Image fusion, multi-scale feature extraction	Integrates different imaging modalities for comprehensive tumour analysis	Improves classification confidence by 25%	Supports holistic patient assessment and multidisciplinary diagnosis	High computational demand; alignment and fusion errors affect interpretation

Table 6 (continued)

Deep learning model	Image processing technique	Key functionality	Performance enhancement	Clinical implications	Limitations and considerations
Transformer-based models	Self-attention mechanism, positional encoding	Captures global dependencies in brain tumour images	Outperforms CNNs in large datasets with better contextual learning	Enables AI-driven diagnostic decision-making in radiology	Requires extensive training data; it sensitive to input variability and lacks spatial detail

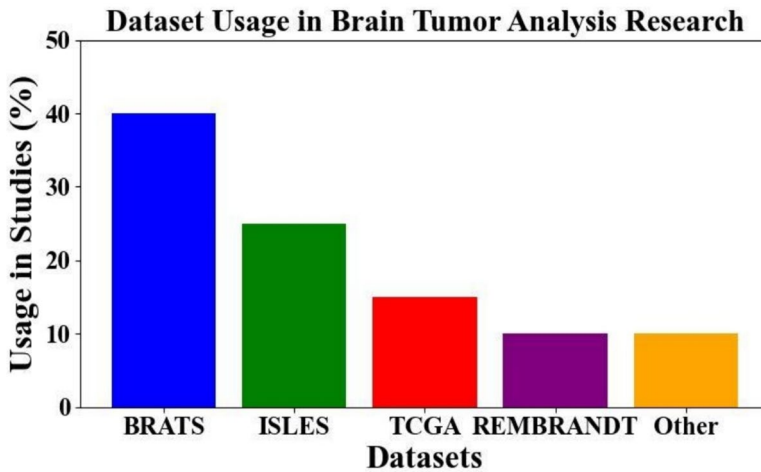


Fig. 6 Analysis of dataset usage in brain tumour analysis research

3.3.3 Fusion of DL with Optimization or Metaheuristic Techniques

A notable hybrid trend involves combining DL models with optimization/metaheuristic algorithms to improve model robustness and convergence. [32] incorporated Particle Swarm Optimization (PSO) to tune CNN parameters, enhancing tumour classification precision. [49, 50] fused PSO with Extreme Learning Machines (ELMs) for fast and efficient segmentation. [51] employed fuzzy clustering optimized using swarm intelligence, showcasing a synergy between biologically inspired algorithms and DL. [57] introduced a novel approach integrating ant colony optimization for parameter tuning, further improving segmentation accuracy and stability.

3.3.4 Multimodal and Multi-task Learning Frameworks

Multimodal learning, where T1, T2, FLAIR, and T1c MRI sequences are combined, allows better tumour delineation and classification. [35] and [39] effectively utilized multi-view or multi-sequence inputs to capture complementary information. [43] and [40] implemented multi-task learning, jointly performing segmentation and classification, which improved cross-task feature generalization. [54] further enhanced this by combining spatial and texture-based learning for multi-class tumour analysis. These frameworks also reduce inference time and model size, making them appropriate for distribution in clinical settings with resource constraints.

3.4 Role of Explainable AIs in Brain Tumour Detection

XAI has gained substantial consideration in medical image analysis, especially in BT segmentation and classification systems, due to its ability to enhance transparency, interpretability, and trustworthiness of DL models. Traditional architectures

like CNNs and transformers often operate as “black-box” systems, making their decision processes opaque and less reliable for clinical deployment. To address this limitation, numerous XAI methodologies have been proposed. [93] introduced local interpretable frameworks that reveal salient image regions influencing model decisions in emergency stroke triage. [94] leveraged DeepLIFT to attribute classification outcomes back to specific MRI pixel regions. [95] and [96] emphasized architectural comparisons and Gradient weighted Class Activation Mapping (Grad-CAM)-based heatmaps to expose tumour-contributing regions. [97] highlighted the role of human-in-the-loop strategies, enhancing diagnostic feedback through visual interpretation mechanisms. [98] applied Layer-wise Relevance Propagation (LRP) to assign pixel-level relevance, thereby improving transparency. Similarly, [99] incorporated explainable CNNs in prediction pipelines for better clarity. Transformer-based segmentation models such as SwinUNETR by [100] introduced non-local attention modules that further supported interpretability. Region-focused classification systems by [101] and model-agnostic interpretations by [102] contributed to practical AI transparency in MRI-based tumour detection. [103] proposed multi-perspective explainability in segmentation frameworks, while [104] and [105] offered hybrid solutions combining vision transformers, ensemble learning, and TL, enriched by XAI. Table 7 depicts the comparative analysis of XAI techniques in BT Analysis.

To further dissect the model’s decision-making processes, different XAI techniques were applied, namely SHAP, LIME, and Grad-CAM, to interpret how internal representations influence output predictions:

- SHAP values estimate the impact of each feature on a model’s prediction by approximating Shapley values, a concept derived from cooperative game theory. Using a Deep Explainer initialized with trained model and background data, SHAP helps identify key pixel-level influences on test image predictions. These insights provide a fine-grained understanding of model decisions and enhance interpretability by visualizing decision boundaries across the neural network.
- LIME is a model-agnostic method that explains local prediction behaviour by creating perturbed samples of a test image and approximating model output using an interpretable surrogate. By highlighting influential features in localized regions, LIME visualizations enhance the clarity of predictions at the instance level, making the model more transparent and user-trustworthy.
- **Grad-CAM** is widely used in image classification, Grad-CAM produces heatmaps from the gradients of a target layer, often the final convolutional one, to indicate spatial regions that contributed most to the prediction. By overlaying these maps on original input images, it becomes possible to visualize critical tumour regions influencing classification, thus strengthening the clinical relevance and reliability of the model outputs. Moreover, the sample visualization of these XAI models is provided in Fig. 7.

These integrated XAI methods offer critical insight into the behaviour of DL models in brain tumour analysis, ensuring that decisions are not only accurate but also interpretable and explainable for clinical validation and trust.

Table 7 Comparison of XAI techniques in BT analysis

XAI technique	Key concept	Application in brain tumour segmentation and classification	Advantages	Limitations
Local Interpretable Model-Agnostic Explanations (LIME)	Perturbation-based local approximation	Highlights important pixel regions contributing to AI's decision	Model-agnostic, interpretable for clinicians	Computationally expensive, local explanations vary
Shapley Additive Explanations (SHAP)	Game-theory based feature attribution	Assigns importance scores to MRI pixels influencing tumour classification	Global interpretability, theoretical foundation	High computation for deep models
Grad-CAM	Utilizes gradients to generate heatmaps	Visualizes relevant regions in MRI scans used for classification	Works with CNNs, easy to interpret	Requires specific DL architectures
Deep LIFT (DL Important Features)	Backpropagation-based relevance mapping	Tracks contributions of each neuron to the model's final decision	Faster than SHAP, suitable for deep networks	Sensitive to model architecture
LRP	Distributes relevance scores across layers	Breaks down AI predictions into interpretable steps	Works well with hierarchical models	It was not generalized to all architectures
Attention-based XAI	Integrates self-attention for feature attribution	Highlights key tumour regions in transformer-based models	Enhances explainability in ViTs	Limited research in medical AI
Transformer Explainability Methods	Uses attention weights to identify key image regions	Explains segmentation/classification in vision transformers	Suitable for ViTs, captures global dependencies	Needs further validation

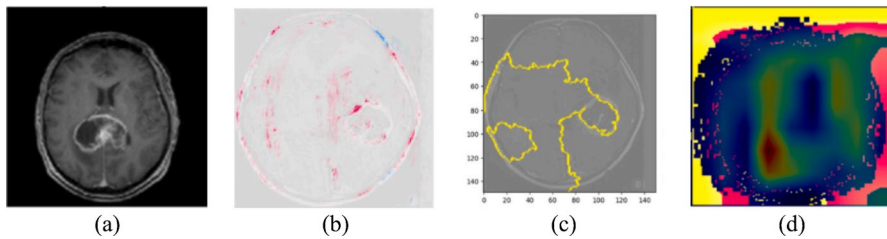


Fig. 7 Explainability visualization of **a** input brain image, **b** SHAP, **c** LIME, and **d** Grad-CAM

3.4.1 Case Study of XAI Usage

The application of XAI in BT detection has become vital for bridging the gap between complex DL models and clinical usability. A notable case study by [93] evaluated a DL-based triage system for severe ischemic stroke in emergency room MRI scenarios, where XAI was employed to interpret and validate model predictions, demonstrating how visual explanations support timely and transparent clinical decisions. Similarly, [101] proposed a region-based explainability model for brain tumour classification, offering case-level insights into model focus regions, thus enhancing trust and interpretability. In another relevant study, [99] developed a CNN-based classification framework augmented with XAI tools like Grad-CAM to provide visual justifications, making the decision-making process clearer for radiologists.

Expanding on this direction, [100] introduced SwinVNETR, a hybrid Swin Transformer-VNet model integrated with non-local blocks and explainability layers to highlight tumour boundaries more accurately. [105] also proposed an ensemble-based approach combining vision transformers and TL, all embedded within an XAI-enabled pipeline to clarify classification outputs and highlight attention regions. Additional contributions by [103] and [104] focused on segment-wise and feature-wise interpretation of tumour data using XAI techniques, emphasizing their role in demystifying model behaviour. These collective findings from real-world and research-based case studies confirm that XAI is not merely an add-on but a foundational tool for enhancing reliability, interpretability, and adoption of DL models in BT diagnostics.

4 Discussion

Based on our comprehensive review, this section critically discusses and evaluates the role of ML and DL, hybrid, and XAI technologies in BT diagnosis and classification. The analysis is structured to highlight key performance trends, model comparisons, offering deeper insights into that traditional and hybrid DL models contribute to advancing automated BT analysis.

4.1 Performance Summary and Benchmarking

Across the reviewed studies, traditional CNN architectures like VGGNet, ResNet, and DenseNet demonstrated strong baseline accuracy for BT classification and segmentation, particularly on benchmark datasets like BraTS, TCGA, and Figshare. TL and pretrained models further improved performance in scenarios with limited labelled data, achieving over 90% accuracy in several comparative studies [70–75]. Hybrid models integrating transformers [68, 76] and attention modules [77–81] have surpassed conventional frameworks, offering improved Dice coefficients and F1-scores on volumetric MRI datasets. Optimized CNNs, including those enhanced via metaheuristics [82–85], consistently outperformed baseline models, particularly in terms of sensitivity and tumour boundary delineation. However, variability in preprocessing, dataset heterogeneity, and training setups often made direct comparisons challenging, highlighting the need for standardized evaluation protocols. Various brain tumour detection models' accuracy rates are presented in Fig. 8. In Fig. 8a, atlas-based accuracy is outlined. Notably, the analysis reveals that the research conducted by PSO-ELM (2022) [44] attains the superior accuracy of 99%, followed by WFKM (2023) [48], RVM-SVM (2023) [49], Hybrid DAE (2020) [37], and DBCWMF (2020). [38] have achieved an accuracy rate of 96%, outperforming alternative models by using BraTS dataset.

In Fig. 8b, statistical-based accuracy as outlined. Notably, the analysis reveals that the research conducted by CNN (2022) [66] attains the highest accuracy rate at 99.74%, followed by SGC-ARANet (2023) [71] with the second-highest accuracy at 99.4%, surpassing other models. Additionally, research efforts by LWCAR-Net (2022) [67], CNN (2022) [64], and HieDNN (2023) [69] have reached an accuracy of 98% by using TCGA dataset, which outperform other techniques.

4.2 Comparative Analysis of Model Architectures

Traditional CNNs exhibit efficient local feature extraction, yet they struggle with capturing long-range dependencies, which hybrid architectures like CNN-Transformer models overcome through global attention mechanisms. While RNN and LSTM-based models are more suitable for sequential or temporal data, their usage

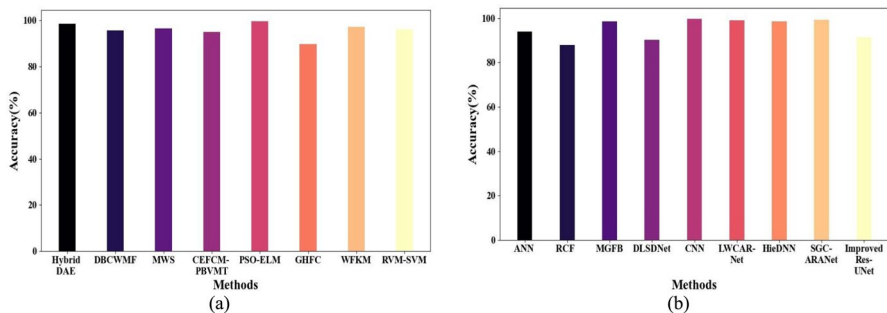


Fig. 8 Accuracy analysis on **a** BraTS dataset and **b** TCGA dataset

in static MRI-based brain tumour analysis remains limited. Graph-based and attention-integrated models improve structural awareness and relational reasoning, especially in complex tumour morphologies [86–89]. Metaheuristic-enhanced models and multimodal networks that fuse radiomic and clinical features offer robustness and adaptability but increase computational overhead. The trade-off among model complexity and interpretability stays a main reflection when selecting architectures for real-world applications. Fig. 9 depicts the analysis of accuracy of different approaches in BT detection by using BraTS dataset.

4.3 Interpretability and Explainability Challenges

Despite performance advancements, most deep learning models function as black boxes, limiting trust in clinical settings. XAI efforts, such as Grad-CAM [99], SHAP [102], and region-based interpretation frameworks [101], offer case-specific insights, but their scalability and reliability are still under investigation. Studies like [103] and [104] highlight the pressure among model difficulty and interpretability, where higher precision often comes at the cost of reduced transparency. The lack of standardized interpretability metrics and inconsistent visualization strategies poses a significant challenge for regulatory validation and clinician acceptance.

4.4 Practical Deployment Considerations

Deploying DL-based brain tumour diagnostic systems in clinical environments demands attention to model generalizability, latency, robustness to noise/artifacts, and compliance with medical imaging standards. Lightweight architectures or edge-compatible CNNs [90–92] offer speed advantages but compromise accuracy. Integration with hospital PACS, real-time inference capabilities, and compliance with

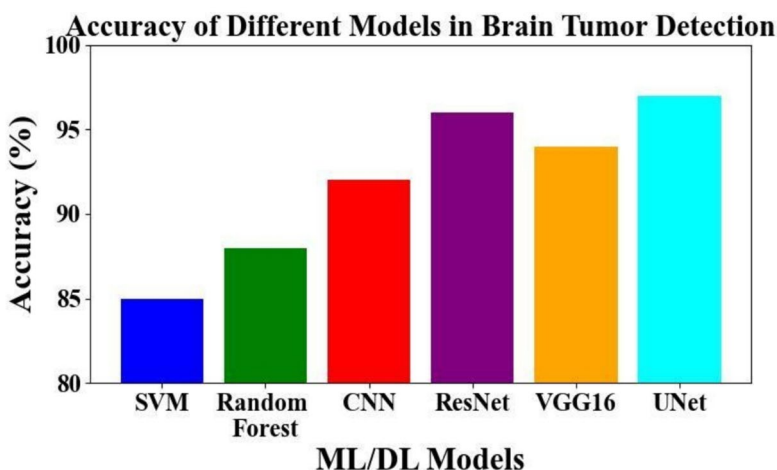


Fig. 9 Analysis of accuracy of various models in BT detection using BraTS dataset

HIPAA/GDPR regulations are essential for deployment. Additionally, continual learning frameworks and federated learning paradigms are emerging to address domain shifts and data privacy challenges, though they are not yet widely adopted in the reviewed literature.

4.5 Mechanistic Insights and Design Trade-Offs

There is a growing shift toward designing approaches that not only perform well but also offer perceptions into biological plausibility. For instance, attention mechanisms in CNN-transformer hybrids mimic clinical focus regions, while graph-based networks implicitly model spatial tumour relationships. However, increased model complexity from multimodal inputs, metaheuristic tuning, or transformer-based backbones leads to greater computational demands and training instability. Balancing interpretability, scalability, and performance remains a key trade-off. Future designs must strive to integrate domain knowledge, lightweight implementation, and transparent decision pathways to ensure effective clinical translation.

5 Open Issues and Research Challenges

This section highlights the existing challenges and unresolved issues in applying ML and DL technologies for BT diagnosis and classification in line with WHO guidelines. Despite significant advancements in ML-based medical imaging, multiple limitations hinder their practical and clinical utility. These challenges come from technical issues, clinical limitations, and ethical concerns, all of which need to be solved to improve diagnosis accuracy and make the system useful in real-world healthcare settings.

5.1 Limitations of Current Survey

Although several ML models show promising results in controlled research environments, this review identifies three key limitations: limited dataset diversity, overfitting on small sample sizes, and minimal clinical validation. Most current studies depend heavily on benchmark datasets (e.g., BraTS), which did not represent the variability in real-world clinical data, thereby reducing generalizability.

5.2 Real-World Challenges in Clinical Integration

Bridging the gap between high-performing machine learning models in controlled laboratory environments and their practical deployment in real-world clinical settings stays a multifaceted challenge. One major barrier lies in the limited generalizability of these models across heterogeneous, multi-center datasets, which often vary in imaging protocols and patient demographics. In addition, real-time processing remains difficult due to high computational anxieties and the lack of advanced infrastructure in many healthcare institutions. Regulatory compliance poses another

significant hurdle, with complex and region-specific approval processes that delay integration into clinical workflows. Beyond technical and regulatory aspects, the successful adoption of AI systems hinges on clinician trust and acceptance. Many healthcare professionals are hesitant to rely on “black-box” models, especially when diagnostic decisions lack transparency or explainability. Concerns regarding accountability, workflow disruption, and job displacement further contribute to resistance. Therefore, future development must prioritize lightweight, interpretable, and clinically aligned models, supported by ongoing medical training and clearly defined regulatory pathways, to ensure both effectiveness and acceptance in real-world medical practice.

5.3 XAI Limitations and Interpretability Gap

A major concern is the interpretability gap of high-performing DL models. While models attain high performance, their “black-box” nature restricts their acceptance among clinicians. The lack of clear explanations for decision-making outcomes raises concerns about accountability and clinical trust in AI systems.

5.4 Key Research Gaps in Brain Tumour Analysis

This section emphasizes upcoming information challenges and pending issues in BT diagnosis and classification using DL. As shown in Fig. 10, some key challenges are discussed in detail.

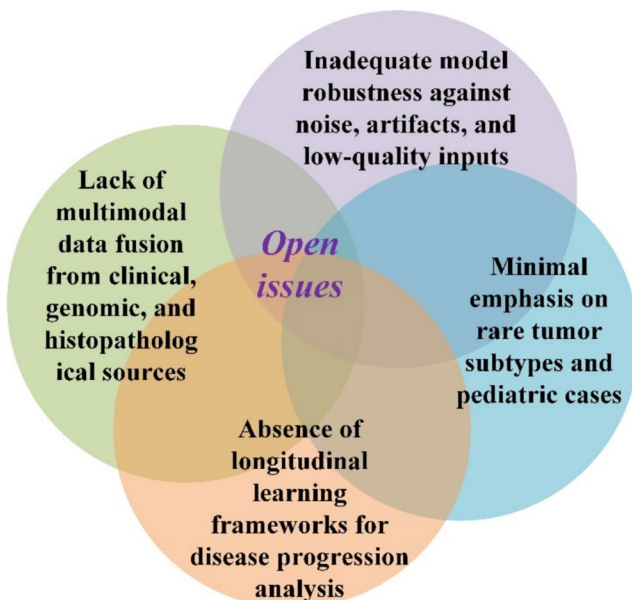


Fig. 10 Open issues in BT analysis

5.5 Future Research Directions

To address these gaps and push the frontier of ML-driven brain tumour analysis, the following future research directions are proposed:

- **Federated Learning and Privacy-Aware Architectures:** Encourage the use of privacy-preserving learning frameworks like federated or blockchain-enhanced ML for collaborative training without compromising patient confidentiality.
- **Clinically-Validated XAI Systems:** Develop clinically interpretable AI models that provide saliency maps, attention mechanisms, or case-based reasoning for transparent decision-making.
- **Multimodal and Longitudinal Integration:** Incorporate multi-source data (e.g., MRI, genomics, clinical reports) and longitudinal patient records to build holistic and temporally aware diagnostic models.
- **Data Augmentation and Synthesis:** Utilize generative approaches (e.g., GANs, diffusion models) to synthesize diverse tumour types, improving model training on rare classes and underrepresented demographics.
- **Edge-AI for Real-Time Deployment:** Design lightweight, energy-efficient ML models that are to be deployed in resource-constrained environments, enabling real-time diagnosis and intraoperative support.
- **Standardization for Clinical Readiness:** Establish guidelines for dataset curation, annotation standards, and clinical validation protocols to ensure reproducibility and trust in AI-assisted diagnostic tools.
- **Cross-Institutional Collaboration Platforms:** Facilitate cross-institutional research by developing secure, scalable platforms that support the sharing of anonymized and annotated data across regions and disciplines.

6 Summary

Developing accurate and reliable BT segmentation and classification systems using ML, DL, hybrid, and XAI techniques remains a complex and evolving challenge. This survey provides a comprehensive review of various atlas-based, statistical, and DL-driven approaches for BT diagnosis, with a clear emphasis on the datasets used, design motivations, and reported accuracies. The methods are systematically categorized and analysed based on their technical advantages, limitations, and practical applicability. Automated segmentation approaches, especially those based on DL, exhibit powerful feature learning abilities, which make them well-suited for handling intricate medical imaging tasks. Furthermore, the review highlights critical factors such as interpretability, computational efficiency, and real-world deployment considerations. Through a critical comparison of current methodologies, this survey offers meaningful insights to support the creation of reliable, interpretable, and efficient diagnostic systems. These systems extend beyond brain tumour detection to aid in diagnosing a range of neurological conditions such as Parkinson's disease, Alzheimer's, dementia, and stroke using multimodal MRI data.

Author Contribution Both the authors have contributed equally to the work.

Data Availability No datasets were generated or analysed during the current study.

Declarations

Ethical Approval All applicable institutional and/or national guidelines for the care and use of animals were followed.

Consent to Participate For this type of analysis formal consent is not needed.

Conflict of Interest The authors declare no competing interests.

References

1. Vinisha A, Boda R (2025) DeepBrainTumorNet: an effective framework of heuristic-aided brain tumour detection and classification system using residual attention-multiscale dilated inception network. *Biomed Signal Process Control* 100:107180
2. Hechri A, Boudaka A, Hamed A (2024) Improved brain tumour segmentation using modified U-Net model with inception and attention modules on multimodal MRI images. *Australian J Electr Electron Eng* 21:48–58
3. Zebari NA, Mohammed CN, Zebari DA et al (2024) A deep learning fusion model for accurate classification of brain tumours in Magnetic Resonance Images. *CAAI Trans Intell Technol* 9:790–804
4. Vinta SR, Chintalapati PV, Babu GR, Tamma R, Sai Chaitanya Kumar G (2024) EDLNet: Ensemble deep learning network model for Automatic Brain Tumor Classification and segmentation. *J Biomolecular Structure Dynamics* 1–13
5. Nassar SE, Yasser I, Amer HM, Mohamed MA (2024) A robust MRI-based brain tumor classification via a hybrid deep learning technique. *J Supercomput* 80:2403–2427
6. Manjunathan N, Gomathi N (2023) Effective image segmentation through MRI with fuzzy-based cell detection using Deep Learning. *Soft Comput* :1–0
7. Asif S, Zhao M, Tang F, Zhu Y (2023) An enhanced deep learning method for multi-class brain tumor classification using Deep Transfer Learning. *Multimed Tools Appl* 82:31709–31736
8. Khan MU, Khan H, Arshad A, Baloch NK, Shaheen A, Tariq F (2021) Brain tumor detection based on magnetic resonance imaging analysis using segmentation, thresholding and morphological operations. 2021 6th International Multi-Topic ICT Conference (IMTIC) 1–6
9. Zheng X, Chen T (2023) High spatial resolution remote sensing image segmentation based on the multiclassification model and the binary classification model. *Neural Comput Appl* 35:3597–3604
10. Kumar KS, Singh NP (2023) Retinal disease prediction through blood vessel segmentation and classification using ensemble-based Deep Learning Approaches. *Neural Comput Appl* 35:12495–12511
11. Tran TS, Nguyen SD, Lee HJ, Tran VP (2023) Advanced crack detection and segmentation on bridge decks using Deep Learning. *Construction Building Mater* 400:132839
12. Gharehchobogh BK, Kuzekanani ZD, Sobhi J, Khiavi AM (2023) Flotation froth image segmentation using mask R-CNN. *Miner Eng* 192:107959
13. Al-qazzaz S, Sun X, Yang H, Yang Y, Xu R, Nokes L, Yang X (2021) Image classification-based brain tumour tissue segmentation. *Multimed Tools Appl* 80:993–1008
14. Ali M, Gilani SO, Waris A, Zafar K, Jamil M (2020) Brain tumour image segmentation using Deep Networks. *IEEE Access* 8:153589–153598
15. Kurmi Y, Chaurasia V (2020) Classification of magnetic resonance images for brain tumour detection. *IET Image Process* 14:2808–2818
16. Abdullah MA, Alkassar S, Jebur B, Chambers J (2021) LBTS-net: a fast and accurate CNN model for Brain Tumour segmentation. *Healthcare Technol Lett* 8:31–36
17. Mano A, Anand S (2020) Method of multi-region tumour segmentation in Brain MRI images using grid-based segmentation and weighted bee swarm optimisation. *IET Image Process* 14:2901–2910

18. Nayak DR, Padhy N, Mallick PK, Bagal DK, Kumar S (2022) Brain tumour classification using noble deep learning approach with parametric optimization through metaheuristics approaches. *Comput* 11:10
19. Soleymanifard M, Hamghalam M (2022) Multi-stage glioma segmentation for tumour grade classification based on Multiscale Fuzzy C-means. *Multimed Tools Appl* 81:8451–8470
20. Pedada KR, A. BR, Patro KK, Allam JP, Jamjoom MM, Samee NA (2023) A novel approach for brain tumour detection using deep learning based technique. *Biomed Signal Process Control* 82:104549
21. Saeedi S, Rezayi S, Keshavarz H, Sharareh R, Niakan K (2023) MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques. *BMC Med Inform Decision Making* 23:16
22. Soomro TA, Zheng L, Afifi AJ, Ali A, Soomro S, Yin M, Gao J (2022) Image segmentation for MR brain tumor detection using machine learning: a review. *IEEE Rev Biomed Eng* 16:70–90
23. Sandhiya B, Raja SK (2024) Deep learning and optimized learning machine for brain tumor classification. *Biomed Signal Process Control* 89:105778
24. Tahosin MS, Sheakh MA, Islam T, Lima RJ, Begum M (2023) Optimizing brain tumor classification through feature selection and hyperparameter tuning in machine learning models. *Inform med unlocked* 43:101414
25. Solanki S, Singh UP, Chouhan SS (2023) Brain tumor classification using ML and DL approaches. In *2023 IEEE 5th international conference on cybernetics, cognition and machine learning applications (ICCCMLA)* :204–208.
26. Amin J, Sharif M, Raza M, Yasmin M (2024) Detection of brain tumor based on features fusion and machine learning. *J Amb Intell Human Comput* :1–7.
27. Sarkar A, Maniruzzaman M, Alahe MA, Ahmad M (2023) An effective and novel approach for brain tumor classification using AlexNet CNN feature extractor and multiple eminent machine learning classifiers in MRIs. *J Sens* 2023:1224619
28. Celik M, Inik O (2024) Development of hybrid models based on deep learning and optimized machine learning algorithms for brain tumor multi-classification. *Exp Syst Appl* 238:122159
29. Remzan N, Tahiry K, Farchi A (2024) Advancing brain tumor classification accuracy through deep learning: harnessing radimagenet pre-trained convolutional neural networks, ensemble learning, and machine learning classifiers on MRI brain images. *Multimed Tools Appl* 83:82719–82747
30. Kareem SW, Bikhitiyar FA, Hawezi RS, Khoshaba FS, Askar S, Muheden KM, Abdulkhaleq IS (2023) Comparative evaluation for detection of brain tumor using machine learning algorithms. *IAES Int J Artif Intell* 12:469
31. Neelima G, Chigurukota DR, Maram B, Girirajan B (2022) Optimal deepmrseg based tumor segmentation with Gan for Brain Tumor Classification. *Biomed Signal Process Control* 74:103537
32. Ali M, Hussain Shah J, Attique Khan M, Alhaisoni M, Tariq U, Akram T, Jin Kim Y, Chang B (2022) Brain tumor detection and classification using PSO and Convolutional Neural Network. *Comput Mater Continua* 73:4501–4518
33. Barzegar Z, Jamzad M (2021) WLFS: Weighted label Fusion Learning Framework for glioma tumor segmentation in Brain Mri. *Biomed Signal Process Control* 68:102617
34. Haq EU, Jianjun H, Li K, Haq HU, Zhang T (2021) An MRI-based deep learning approach for efficient classification of brain tumors. *J Amb Intell Human Comput* 14:6697–6718
35. Ottom MA, Rahman HA, Dinov ID (2022) Znet: Deep Learning Approach for 2D MRI brain tumor segmentation. *IEEE J Trans Eng Health Med* 10:1–8
36. Vankdothu R, Hameed MA (2022) Brain tumor segmentation of MR images using SVM and fuzzy classifier in machine learning. *Measurement: Sensors* 24:100440
37. Khan F, Gulzar Y, Ayoub S, Majid M, Mir MS, Soomro AB (2023) Least square-support vector machine based brain tumor classification system with multi model texture features. *Frontiers Appl Math Statistics* 9:1324054
38. Islam MK, Ali MS, Miah MS, Rahman MM, Alam MS, Hossain MA (2021) Brain tumor detection in MR image using superpixels, principal component analysis and template based K-means clustering algorithm. *Machine Learning with Applications* 5:100044
39. Aurna NF, Yousuf MA, Taher KA, Azad AKM, Moni MA (2022) A classification of MRI brain tumor based on two stage feature level ensemble of deep CNN Models. *Comput Biol Med* 146:105539
40. Zhu Z, Attique Khan M, Wang S-H, Zhang Y-D (2023) RBEBT: a ResNet-based BA-Elm for brain tumor classification. *Computers, Materials & Continua* 74:101–111

41. Yogananda CG, Shah BR, Vejdani-Jahromi M et al (2020) A fully automated deep learning network for Brain Tumor Segmentation. *Tomography* 6:186–193
42. Siva Raja PM, Rani AV (2020) Brain tumor classification using a hybrid deep autoencoder with bayesian fuzzy clustering-based segmentation approach. *Biocyberne Biomed Eng* 40:440–453
43. Dandu JR, Thiagarajan AP, Murugan PR, Govindaraj V (2020) Brain and pancreatic tumor segmentation using SRM and BPNN classification. *Health Technol* 10:187–195
44. Aboelenen NM, Songhao P, Koubaa A, Noor A, Afifi A (2020) HTTU-net: hybrid two track U-Net for automatic brain tumor segmentation. *IEEE Access* 8:101406–101415
45. Wu W, Li D, Du J, Gao X, Gu W, Zhao F, Feng X, Yan H (2020) An intelligent diagnosis method of brain MRI tumor segmentation using deep convolutional neural network and SVM algorithm. *Comput Math Meth Med* 2020:1–10
46. Sivakumar V, Janakiraman N (2020) A novel method for segmenting brain tumor using modified watershed algorithm in MRI image with FPGA. *Biosyst* 198:104226
47. Debnath S, Talukdar FA, Islam M (2021) Combination of contrast enhanced fuzzy c-means (CEFCM) clustering and pixel based voxel mapping technique (PBVM) for three dimensional brain tumour detection. *J Amb Intell Human Comput* 12:2421–2433
48. Huang Z, Liu Y, Song G, Zhao Y (2021) Gammanet: an intensity-invariance deep neural network for computer-aided brain tumor segmentation. *Optik* 243:167441
49. Mohapatra SK, Sahu P, Almotiri J, Alroobaea R, Rubaiee S, Bin Mahfouz A, Senthilkumar AP (2022) Segmentation and classification of encephalon tumor by applying improved fast and robust FCM algorithm with PSO-based Elm Technique. *Comput Intell Neurosci* 2022:1–9
50. Sathish P, Elango NM (2022) Gaussian hybrid fuzzy clustering and radial basis neural network for automatic brain tumor classification in MRI images. *Evol Intell* 15:1359–1377
51. Iqbal M, Anwar M, Iftikhar M, Gilanie G, Bajwa U (2022) Automatic brain tumor segmentation from magnetic resonance images using superpixel-based approach. *Multimed Tools Appl* 87:38409–38427
52. Alqazzaz S, Sun X, Nokes LD, Yang H, Yang Y, Xu R, Zhang Y, Yang X (2022) Combined features in region of interest for Brain Tumor segmentation. *J Digit Imaging* 35:938–946
53. Chahal PK, Pandey S (2023) A hybrid weighted fuzzy approach for brain tumor segmentation using Mr Images. *Neural Comput Appl* 35:23877–23891
54. Dixit A, Thakur MK (2023) RVM-mr image brain tumour classification using novel statistical feature extractor. *Int J Inf Technol* 15:2395–2407
55. Alagarsamy S, Govindaraj V, Senthilkuma A (2023) Automated brain tumor segmentation for mr brain images using artificial bee colony combined with interval type-II fuzzy technique. *IEEE Trans Ind Inform* 19:11150–11159
56. Kharaji M, Abbasi H, Orouskhani Y, Shomalzadeh M, Kazemi F, Orouskhani M (2024) Brain tumor segmentation with advanced NNU-net: pediatrics and adults tumors. *Neurosci Inform* 4:100156
57. Sekkate S, Khalil M, Adib A (2023) A statistical feature extraction for deep speech emotion recognition in a bilingual scenario. *Multimed Tools Appl* 82:11443–11460
58. Dogu E, Albayrak YE, Tuncay E (2021) Length of hospital stay prediction with an integrated approach of statistical-based fuzzy cognitive maps and artificial neural networks. *Med Biol Eng Comput* 59:483–496
59. Faizi MI, Adnan SM (2024) Improved segmentation model for melanoma lesion detection using normalized cross-correlation-based k -means clustering. *IEEE Access* 12:20753–20766
60. Shojaedini SV, Abedini M, Monajemi M (2023) Generative Adversarial Network: a statistical-based deep learning paradigm to improve detecting breast cancer in thermograms. *Med Biological Eng Comput* 62:1077–1087
61. Ali A, Ali A, Abaluof H, Al-Sharu WN, Saraereh OA, Ware A (2023) Moisture detection in tree trunks in semiarid lands using low-cost non-invasive capacitive sensors with statistical based anomaly detection approach. *Sens* 23:2100
62. Bhatia M, Sharma V, Singh P, Masud M (2020) Multi-level P2P traffic classification using heuristic and statistical-based techniques: a hybrid approach. *Symm* 12:2117
63. Rehman A, Harouni M, Karimi M, Saba T, Bahaj SA, Awan MJ (2022) Microscopic retinal blood vessels detection and segmentation using support vector machine and k-nearest neighbors. *Microscopy Res Technique* 85:1899–1914

64. Martos O, Hoque MZ, Keskinarkaus A, Kemi N, Näpänkangas J, Eskuri M, Pohjanen V-M, Kaupila JH, Seppänen T (2023) Optimized detection and segmentation of nuclei in gastric cancer images using stain normalization and blurred artifact removal. *Pathology - Res Pract* 248:154694
65. Patel RK, Kashyap M (2022) Automated diagnosis of COVID stages from lung CT images using statistical features in 2-dimensional flexible analytic wavelet transform. *Biocybern Biomed Eng* 42:829–841
66. Zeineldin RA, Karar ME, Coburger J, Wirtz CR, Burgert O (2020) DeepSeg: Deep Neural Network Framework for automatic brain tumor segmentation using magnetic resonance Flair images. *Int J Comput Ass Rad Surgery* 15:909–920
67. Pitchai R, Supraja P, Victoria AH, Madhavi M (2021) Brain tumor segmentation using deep learning and fuzzy K-means clustering for magnetic resonance images. *Neural Process Lett* 53:2519–2532
68. Barzegar Z, Jamzad M (2020) A reliable ensemble-based classification framework for Glioma Brain Tumor Segmentation. *Signal, Image Video Process* 14:1591–1599
69. Singh R, Goel A, Raghuvanshi DK (2021) Computer-aided diagnostic network for brain tumor classification employing modulated Gabor Filter Banks. *Visual Comput* 37:2157–2171
70. Liu H, Li Q, Wang I-C (2021) A deep-learning model with learnable group convolution and deep supervision for Brain Tumor Segmentation. *Math Problems Eng* 2021:1–11
71. Chattopadhyay A, Maitra M (2022) MRI-based brain tumour image detection using CNN based Deep Learning Method. *Neurosci Inform* 2:100060
72. Tankala S, Pavani G, Biswal B, Siddhartha G, Sahu G, Subrahmanyam NB, Aakash S (2022) A novel depth search based light weight car network for the segmentation of brain tumour from mr images. *Neurosci Inform* 2:100105
73. Ge T, Zhan T, Li Q, Mu S (2022) Optimal Superpixel kernel-based kernel low-rank and sparsity representation for brain tumour segmentation. *Comput Intell Neurosci* 2022:1–12
74. Shajin FH, Salin P, Rajesh P, Nagoji Rao VK (2023) Efficient framework for brain tumour classification using hierarchical deep learning neural network classifier. *Comput Meth Biomechanics Biomed Eng Imaging Visualization* 11:750–757
75. Liu Z, Ma C, She W, Wang X (2023) Transmvu: multi-view 2D u-nets with Transformer for Brain Tumour segmentation. *IET Image Process* 17:1874–1882
76. Karri M, Annvarapu CS, Acharya UR (2023) SGC-aranet: scale-wise global contextual axile reverse attention network for Automatic Brain Tumor Segmentation. *Appl Intell* 53:15407–15423
77. Mahesh Kumar G, Parthasarathy E (2023) Development of an enhanced U-net model for brain tumor segmentation with optimized architecture. *Biomed Signal Process Control* 81:104427
78. Xu M-C, Zhou Y, Jin C, De Groot M, Alexander DC, Oxtoby NP, Jacob J (2023) Mismatch: calibrated segmentation via consistency on differential morphological feature perturbations with limited labels. *IEEE Trans Med Imaging* 42:2988–2999
79. Li X, Fang Z, Zhao R, Mo H (2024) Brain tumor MRI segmentation method based on improved RES-unet. *IEEE J Radio Frequency Identification* 8:652–657
80. Tabatabaei S, Rezaee K, Zhu M (2023) Attention transformer mechanism and fusion-based deep learning architecture for MRI Brain Tumor Classification System. *Biomed Signal Process Control* 86:105119
81. Poornam S, Angelina JJ (2024) Vitalt: a robust and efficient brain tumor detection system using vision transformer with attention and linear transformation. *Neural Comput Appl* 36:6403–6419
82. Dutta TK, Nayak DR, Pachori RB (2024) GT-NET: Global Transformer Network for multiclass brain tumor classification using mr images. *Biomed Eng Lett* 1–9
83. Aboussaleh I, Riffi J, Fazazy KE, Mahraz AM, Tairi H (2024) STCPU-net: Advanced U-shaped deep learning architecture based on Swin Transformers and Capsule Neural Network for brain tumor segmentation. *Neural Comput Appl* 36:18549–18565
84. Zhang Z, Wu H, Zhao H, Shi Y, Wang J, Bai H, Sun B (2023) A novel deep learning model for medical image segmentation with convolutional neural network and Transformer. *Interdisciplinary Sci Comput Life Sci* 15:663–677
85. Zhang S, Ren B, Yu Z, Yang H, Han X, Chen X, Zhou Y, Shen D, Zhang X-Y (2022) TW-net: Transformer weighted network for Neonatal Brain MRI segmentation. *IEEE J Biomed Health Inform* 27:1072–1083
86. Joshi A, Sharma KK (2024) Dense deep transformer for medical image segmentation: Ddtrams. *Multimed Tools Appl* 83:18073–18089

87. Shi J, Yu L, Cheng Q, Yang X, Cheng K-T, Yan Z (2023) MFTrans: modality-masked fusion transformer for incomplete multi-modality brain tumor segmentation. *IEEE J Biomed Health Inform* 28:379–390
88. El-Feshawy SA, Saad W, Shokair M, Dessouky M (2023) IOT framework for brain tumor detection based on optimized modified resnet 18 (OMRES). *J Supercomput* 79:1081–1110
89. Kalaiselvi T, Padmapriya ST (2022) Multimodal MRI brain tumor segmentation—a ResNet-based U-Net approach. *Brain Tumor MRI Image Segmentation Using Deep Learning Techniques* 123–135
90. Ananda Kumar KS, Prasad AY, Metan J (2022) A hybrid deep CNN-COV-19-res-net transfer learning architype for an enhanced brain tumor detection and classification scheme in medical image processing. *Biomed Signal Process Control* 76:103631
91. Sharma AK, Nandal A, Dhaka A, Zhou L, Alhudhaif A, Alenezi F, Polat K (2023) Brain tumor classification using the modified RESNET50 model based on Transfer learning. *Biomed Signal Process Control* 86:105299
92. Saha A, Zhang Y-D, Satapathy SC (2021) Brain tumour segmentation with a muti-pathway ResNet based unet. *J Grid Comput* :1–0.
93. Kim J, Oh SW, Lee HY, Choi MH, Meyer H, Huwer S, Zhao G, Gibson E, Han D (2024) Assessment of deep learning-based triage application for acute ischemic stroke on brain MRI in the ER. *Acad Radiol* 31:4621–4628
94. Gu Y, Li Y, Gao L (2024) Association between tumor markers elevation and poor functional outcomes after acute ischemic stroke: a longitudinal stroke center-based study. *Annals Med* 56:2426753
95. Sachdeva J, Sharma D, Ahuja CK (2024) Comparative analysis of different deep convolutional neural network architectures for classification of brain tumor on Magnetic Resonance Images. *Arch Comput Methods Eng* 31:1959–1978
96. Reyes D, Sánchez J (2024) Performance of convolutional neural networks for the classification of brain tumors using magnetic resonance imaging. *Heliyon* 10.
97. Ye J, Zhao Z, Ghafourian E, Tajally A, Alkhazaleh HA, Lee S (2024) Optimizing the topology of Convolutional Neural Network (CNN) and Artificial Neural Network (ANN) for Brain tumor diagnosis (BTD) through mris. *Heliyon* 10.
98. Aljohani M, Bahgat WM, Balaha HM, AbdulAzeem Y, El-Abd M, Badawy M, Elhosseini MA (2024) An automated metaheuristic-optimized approach for diagnosing and classifying brain tumors based on a convolutional neural network. *Results Eng* 23:102459
99. Nazir MI, Akter A, Wadud MA, Uddin MA (2024) Utilizing customized CNN for brain tumor prediction with explainable AI. *Heliyon* 10.
100. Maria Nancy A, Sathyarajasekaran K (2024) SwinVNETR: Swin V-net Transformer with non-local block for volumetric MRI Brain Tumor Segmentation. *Automatika: časopis za automatiku, mjerenje, elektroniku, računarstvo i komunikacije* 65:1350–63.
101. Narayankar P, Baligar VP (2024) Explainability of brain tumor classification based on region. In2024 International Conference on Emerging Technologies in Computer Science for Interdisciplinary Applications (ICETCS) :1–6.
102. Ariful Islam M, Mridha MF, Safran M, Alfahood S, MohsinKabir M (2025) Revolutionizing brain tumor detection using explainable AI in MRI images. *NMR in Biomed* 38:e70001
103. Hassan M, Fateh AA, Lin J, Zhuang Y, Lin G, Xiong H, You Z, Qin P, Zeng H (2024) Unfolding explainable AI for brain tumor segmentation. *Neurocomput* 599:128058
104. Kaushal S, Gaur H, Bhati G, Rai AK (2024) Explainable artificial intelligence for brain tumor detection. In2024 2nd International Conference on Advances in Computation, Communication and Information Technology (ICAICIT) 1:965–969.
105. Hossain S, Chakrabarty A, Gadekallu TR, Alazab M, Piran MJ (2023) Vision transformers, ensemble model, and transfer learning leveraging explainable ai for brain tumor detection and classification. *IEEE J Biomed Health Informat* 28:1261–1272

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.