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Advanced MRI-based deep learning for brain tumors: a five-year review of oncology–radiology–AI synergy

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ABSTRACT

Rapid advancements in computer vision and machine learning have significantly revolutionized medical imaging one such application is brain tumor detection and classification. Deep learning has emerged as a powerful tool, which offers exceptional capabilities in handling complex medical datasets. However, the current systems still face challenges in achieving optimal accuracy, robustness and clinical interpretability. This study presents a comprehensive survey of brain tumor segmentation, classification and detection techniques using deep learning, metaheuristic and hybrid approaches. The detailed quantitative evaluations of conventional and emerging methods are conducted by examining key performance metrics, dataset characteristics, strengths, and limitations. This review highlights recent breakthroughs by analyzing state-of-the-art techniques from the past five years, research gaps and potential directions for future advancements. These findings provide insights into novel architectures, optimization strategies and clinical applications which ultimately guide researchers towards more robust, interpretable and clinically impactful artificial intelligence (AI)-driven solutions for brain tumor analysis.

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1. INTRODUCTION

Brain tumors represent a formidable clinical challenge due to their biological complexity, high mortality rates and the variability in symptoms and treatment responses. These tumors whether primary in origin or metastatic differ widely in their histology, location, and aggressiveness, making accurate diagnosis and classification crucial for effective intervention. Among these, artificial intelligence (AI) specifically approaches like convolutional neural networks (CNNs) has demonstrated unprecedented potential in automating tumor detection, segmentation and classification. World Health Organization (WHO) classifies brain tumors based on their histological features into four grades (Grade I to Grade IV), reflecting their malignancy or benignity. When detecting brain tumors, magnetic resonance imaging (MRI) is used to identify structural abnormalities and pathologies that underpin neurological conditions. Medical professionals, such as neurologists, rely on these images to make diagnoses and recommend treatment plans. The integration of semi-automatic and automatic methods has increasingly supported medical image processing for enhanced diagnostic accuracy. This manuscript is a review article that synthesizes recent advances in brain tumor segmentation and classification from MRI images, with a focus on deep learning, hybrid machine learning and optimization-based approaches. The review covers studies published between

2020 and 2024, selected for their relevance to medical image analysis, methodological innovation, and reported performance metrics. Table 1 shows recent advancement in techniques or architecture along with results for classifying brain tumors. The contribution, training algorithm, datasets, and limitations of the most used segmentation and classification methods are detailed in Table 2.

Younis *et al*. [1], an automated brain tumor detection and classification approach was proposed leveraging a faster CNN framework built on the VGG-16 architecture for feature extraction. The study employed an ensemble learning strategy, combining multiple models and training sets to enhance predictive performance. Integrating deep learning and transfer learning techniques, the CNN-based model outperformed traditional machine learning approaches.

Ranjbarzadeh *et al*. [2], introduced a cascade CNN (C-ConvNet), designed as a simple yet efficient model for brain tumor classification. The architecture combines local and global features through two distinct processing routes. A distance-wise attention (DWA) methodology was incorporated, which accounts for the spatial influence of the tumor's center and the surrounding brain regions. By employing parallel convolutional layers, the DWA mechanism effectively mitigates overfitting and enhances model generalization.

Shehab *et al*. [3], presented an ensemble approach combining a 3D U-Net and a CNN for brain tumor segmentation. The model deployed leaky ReLUs an instance normalization to improve generalization.

Li *et al*. [4], a radiomics framework was proposed that emphasizes feature selection (FS) to reduce redundancy and improve accuracy. To address the absence of a universal FS method, they introduced triple-factor cascaded selection (TFCS), which applies mutual information to retain highly relevant features while minimizing overlap.

Diao *et al*. [5], developed a joint learning framework that transfers knowledge from complete to single-modality inputs, enabling feature reconstruction and enhancement. This approach was useful in scenarios with missing imaging modalities.

Nayak *et al*. [6], proposed a brain tumor detection model that integrates morphological preprocessing, discrete wavelet transform (DWT) and deep autoencoder techniques. Morphological cropping is first applied to reduce noise and standardize image dimensions. DWT is then utilized for effective feature reduction, addressing the high-dimensional data challenge. The model combines DWT with a stacked deep autoencoder and deep autoencoder convolutional neural network (SDA-DA CNN), enhanced through spectral data augmentation for robust feature extraction and classification.

Kumar *et al*. [7], developed a lightweight deep learning model with an efficient compression technique, integrating black widow optimization (BWO) and whale optimization (WOA). Their method, validated on MRI images, demonstrated strong performance in terms of accuracy and quality.

Özbay and Özbay [8], proposed a precision hashing framework that enhances brain tumor detection by addressing low image resolution and overfitting challenges. The method utilizes a pre-trained DenseNet201 model for feature extraction, combining local discriminative features and public features at the pooling stage through feature fusion. A hash layer is introduced between the fully connected and classification layers to generate robust hash codes. Final classification is performed using a similarity metric, improving both interpretability and model generalization on low-resolution medical images.

Jaspin and Selvan [9], using skull-stripped MRI images implemented a multi-channel convolutional neural network (MCCNN) model for tumor classification. MCCNN performs three operations to categorize tumors. Chaki and Woźniak [10], introduced BTSCNet, a deep learning-based four-stage framework for classifying the tumors such as meningioma, glioma and pituitary tumors.

Dandıl and Karaca [11] proposed a deep learning framework for the binary classification of brain tumors and pseudo-brain tumors using magnetic resonance spectroscopy (MRS) data. Their approach employed a stacked architecture, integrating long short-term memory (LSTM) and bidirectional LSTM (Bi-LSTM) networks to effectively capture temporal dependencies within spectral signals. Chattopadhyay and Maitra [12] proposed a CNN-based algorithm for brain tumor segmentation using 2D MRI scans. After segmentation by the CNN, traditional classifiers such as support vector machines (SVMs) and activation functions like Softmax, RMSProp, and Sigmoid were used to validate and cross-check classification results.

Turk *et al*. [13], using MRI scans proposed a three-stage ensemble deep learning framework. To enhance feature diversity and robustness the system integrates multiple CNN architectures. A binary classification using Monte Carlo cross-validation determines the presence or absence of a tumor in the first stage. The classification of detected tumors into four categories: normal, glioma, meningioma, and pituitary tumor are done in the second stage. To provide visual interpretability the class activation maps (CAMs) are generated for each tumor type.

Qin *et al*. [14], introduced a parallel computing approach for large-scale brain tumor classification using parallel stochastic gradient descent (SGD) and parallel asynchronous stochastic gradient descent (ASGD) algorithms, implemented through a message-passing interface with shared memory architecture. For feature extraction histogram of oriented gradients (HOG) was deployed directly on raw images including skull regions instead of relying on conventional segmentation.

Devi *et al*. [15], for the brain tumor classification, proposed a hybrid deep learning framework using MRI images. For detailed feature extraction the methodology begins with stationary wavelet packet transform (SWPT) and for selecting the most relevant features hybrid adaptive black widow moth flame optimization (HABWMFO) was deployed. The model employs adaptive kernel fuzzy c-means (AKFCM) clustering for segmentation and hybrid CNN-LSTM architecture for classification.

Rammurthy and Mahesh [16] proposed WHHO algorithm, along with WOA and HHO algorithm, aided in better tumor detection. Using cellular automata and rough set theory the segmentation is performed on each input brain MRI image. Kesav and Jibukumar [17], an RCNN-based architecture targeting Glioma, Meningioma and Pituitary tumors was discussed. The model demonstrated fast execution and competitive accuracy compared to leading methods.

Alzahrani [18], presented ConvAttenMixer, a transformer-based model that integrates self-attention and external attention. This dual-attention approach enhanced the outcome of the results. Razzaghi *et al.* [19], for brain tumor detection proposed a multimodal domain adaptation framework. The method introduces a multimodal feature encoder that facilitates knowledge transfer both between and within modalities, enhancing generalization to unseen test domains. However, it leads to increased computational complexity, parameter overhead and challenges due to unbalanced modality data distributions.

Öksüz *et al*. [20], a brain tumor classification approach to differentiate between meningioma, glioma and pituitary tumors and for predicting the 1p/19q co-deletion status in low-grade glioma (LGG) cases by fusing deep and shallow features was proposed. The method leverages rich contextual features by incorporating surrounding tissue in the region of interest (ROI).

Kumar *et al*. [21] introduced a brain tumor detection method combining skull stripping and entropy-based trilateral filtering for preprocessing. The tumor segmentation was done using fuzzy centroid-based region growing, followed by classification via an optimized deep belief network (DBN). The proposed GS-MVO-DBN model outperformed several baseline classifiers including SVM, NN, and CNN.

Kumar *et al.* [22], combined ResNet-152-based transfer learning with Otsu binarization and proposed a hybrid Deep CNN model for noise reduction and image enhancement. Using gray-level co-occurrence matrix (GLCM) method the features were extracted.

Chinnam *et al*. [23], MAC U-Net, a brain tumor segmentation method attention-gated U-Net architectures with Group Normalization was implemented. The system comprises a 9-layer model for full tumor detection from FLAIR and T2 modalities and a 7-layer model for segmenting small tumors from T1-CE images. Decision-level fusion integrates outputs from two phases full tumor segmentation (Phase I) and enhanced/core tumor segmentation (Phase II) to effectively detect low-grade tumors.

Nirmalapriya *et al*. [24], proposed a fully automated hybrid segmentation and classification system for brain tumors. The method fuses U-Net with CFPNet-M, leveraging Tanimoto similarity for accurate tumor segmentation. Training was optimized using aquila spider monkey optimization (ASMO), a blend of SMO and Aquila optimizer. For classification into tumor grades a SqueezeNet model was employed and fine-tuned using fractional aquila spider monkey optimization (FASMO), which integrates SMO, AO, and fractional calculus, enhancing accuracy in distinguishing benign and malignant tumors across four grades.

Kumar and Prince [25], proposed the DBNQLBC technique which is a hybrid model that combined a deep belief network (DBN) with a quadratic logit boost classifier for brain tumor classification. This approach enhanced accuracy, reduced false-positive rates and lowered computational time compared to existing methods.

Bashkandi *et al*. [26] discussed a CNN-based brain tumor detection method optimized using a hybrid of the political optimizer (PO) and particle swarm optimization (PSO). The improved metaheuristic tuning enhances classification accuracy, outperforming methods such as capsule networks, K-means, and genetic algorithms. The model achieved superior performance in melanoma detection.

Pacheco *et al*. [27], considered an automatic brain tumor segmentation pipeline that eliminates the traditional brain extraction (BE) step. Their experiments showed that BE choice can affect segmentation performance by up to 15.7%. By training models directly on non–skull-stripped images, the approach achieved a significant reduction in processing time.

Zheng *et al*. [28], proposed a four-stage pipeline comprising preprocessing, segmentation, feature extraction, and classification. Segmentation leverages optimized Kapur thresholding and mathematical morphology, followed by Zernike moments for feature extraction. A SVM classifier, optimized using a customized arithmetic optimization algorithm (CAOA), delivers the final diagnosis.

Pedada *et al*. [29], introduced a residual U-Net variant that was tested on standard datasets it showed superior performance in both qualitative and quantitative metrics. Sharma *et al*. [30], a modified ResNet50 model that incorporates HOG features from MRI images for brain tumor detection was proposed. The model integrated feature optimization to enhance discriminative neural representations from complex vectors. The approach improved on deep feature extraction accuracy.

Sobhaninia *et al*. [31], proposed a multiscale cascaded multitask network. The model enhances performance using multiscale and cascaded encoder-decoder layers for segmentation and a feature aggregation module to boost classification accuracy. Sarala *et al*. [32], for detecting glioma brain tumors proposed a dual CNN methodology, where the first CNN extracts image features and the second CNN handles classification. For segmentation, a hybrid deep supervised attention HDSA method is applied to isolate the tumor region of interest. Ruba *et al*. [33], to enhance tumor localization proposed JGate-AttResUNet, a novel brain tumor segmentation model integrating a J-Gate attention mechanism. It is evaluated on BRATS 2015 and 2019 datasets, outperforming baseline architectures like UNet, Residual UNet and their attention-gated variants.

Kanchanamala *et al*. [34], for BT detection and classification introduced a dual-method pipeline using exponential deer hunting optimization (ExpDHO). They proposed ExpDHO-based shepard CNN (ShCNN) for detection and an ExpDHO-based deep CNN for classification. The pipeline includes noise removal, segmentation along with data augmentation in preprocessing. The novel ExpDHO algorithm, combining exponential weighted moving average (EWMA) and deer hunting optimization, enhances model convergence and performance, and contributing to accurate tumor localization.

Wang *et al*. [35], for 3D MRI images proposed GAM-Net, a brain tumor segmentation algorithm. The model employs a D-ConvD encoder to extract features from multi-modal MRIs, paired with a gradient extraction (GE) branch to capture fine gradient details. A gradient-driven decoder (GDD) leverages this information to enhance segmentation, especially near tumor boundaries.

Shyamala and Brahmananda [36] discussed and proposed a feature-based classification method detecting different types of tumors from brain images. The extracted features are classified using a generalized regression neural network (GRNN), with tuned hyperparameters to minimize training loss and complexity.

Yogananda *et al*. [37], to perform binary segmentation for individual tumor subcomponents, proposed a fully automated brain tumor segmentation framework using three specialized 3D-Dense-UNets, this integrated strategy simplifies the multiclass segmentation challenge.

Geetha *et al*. [38], proposed a classification framework optimized by the sine cosine archimedes optimization algorithm (SCAOA) a hybrid of AOA and SCA. After Gaussian filtering for noise reduction, SegNet, tuned via SCAOA, performs tumor segmentation. Extracted features are passed to ShCNN for detection, followed by classification into pituitary, glioma, and meningioma types using a SCAOA-optimized DenseNet. The method shows promise for mobile deployment and future hybridization.

Nagarani *et al*. [39], introduced SPGAN-MSOA-CBTMRI, a brain tumor classification method using a self-attention–based progressive GAN optimized by the momentum search optimization algorithm (MSOA). The approach enhances MRI image quality via anisotropic diffusion kuwahara filtering (ADKF). Feature extraction leverages ternary patterns and discrete wavelet transforms to compute six key texture features. SPGAN was then used to classify images into tumor and non-tumor categories.

Balasubramanian *et al*. [40], proposed RFShCNN a hybrid brain tumor detection model, which fuses residual networks with shepherd CNN, enhanced by a regression layer incorporating fractional calculus (FC). Priya and Vasudevan [41], for classification of brain tumors proposed a hybrid deep learning model combining AlexNet for feature extraction and a gated recurrent unit (GRU) network. AlexNet handles spatial feature encoding while GRU mitigates gradient vanishing and models sequential dependencies. Through careful hyperparameter tuning, the model enhances generalization and avoids overfitting. Final classification using softmax layer, effectively categorized tumors into four distinct classes.

Ajay and Gopalan [42], to improve edge detection in MRI images proposed an enhanced sobel edge detection algorithm using an 8-directional template. The method was benchmarked against traditional edge detection techniques using metrics like MSE, RMSE, Entropy, SNR, and PSNR.

Sangui *et al*. [43], for BT detection and segmentation from MRI scan, proposed a model that integrates enhancements to the classic U-Net structure intended at improving segmentation accuracy. Experimental results demonstrate the tailored U-Net outperforms other deep learning models confirming its robustness and precision in tumor localization.

Patil and Kirange [44], proposed an ensemble deep convolutional neural network (EDCNN) by fusing features from a shallow CNN (SCNN) and VGG16; both trained on T1C-modality MRI images. This fusion approach enhanced classification accuracy for three brain tumor types and improved loss convergence.

Khairandish *et al*. [45], to distinguish benign and malignant tumors in MRI images, proposed a hybrid brain tumor classification combining CNN and SVM. After normalization and feature extraction via maximally stable extremal regions (MSER), threshold-based segmentation is applied and labeled features were fed into the CNN-SVM pipeline.

Khan *et al*. [46] proposed a 23-layer CNN which was trained on a large dataset to achieve strong performance. But, with limited data in a second dataset, the model showed signs of overfitting. To mitigate this, they introduced a hybrid approach combining transfer learning with VGG16 and architectural elements of the 23-layer CNN, improving generalization on smaller datasets.

Rahman and Islam [47] proposed the PDCNN framework, a deep learning model. The model was evaluated on the Kaggle and Figshare datasets, handling binary and multiclass classification tasks. PDCNN demonstrated high accuracy, precision, recall, and F1-score, across multiple datasets, indicating its robustness.

Atmakuri *et al*. [48], explored the use of deep learning techniques to predict the phase progression of brain tumors. The approach highlights supervised classification to manage complex tumor behavior and enables prediction of future anomalies. The authors propose that a fully automated system for phase prediction can be developed using existing simulation toolboxes. Islam *et al*. [49], for brain tumor detection in MRI images proposed a template-based K-means clustering approach. The method integrates superpixel segmentation and principal component analysis (PCA) for robust feature extraction, followed by TK-means for precise tumor localization.

Tseng and Tang [50] considered a PSO-XGBoost based brain tumor detection framework, integrating optimized processing and feature selection. MRI images were enhanced using CLAHE, segmented via K-Means clustering and refined with PSO to select critical features. Classification was performed using XGBoost, Naive Bayes, and ID3, with the PSO-XGBoost model achieving standout results highlighting its high reliability in brain tumor identification.

Uke *et al*. [51], presented a brain tumor extraction method from 2D MRI scans using the fuzzy C-Means clustering algorithm for segmentation, followed by classification via traditional machine learning classifiers implemented in scikit-learn. To enhance performance, CNN was also employed using Keras and TensorFlow, which outperformed the traditional models on a real-time dataset. Deepak and Ameer [52] implemented a deep transfer learning-based system using a pre-trained GoogLeNet. These features were fed into traditional classifiers for tumor categorization, with evaluation performed using patient-level five-fold cross-validation.

Naser and Deen [53], for tumor grading, specifically targeting low grade glioma (LGG) in MRI scans, developed a methodology that combines U-Net–based CNN for tumor segmentation and transfer learning with VGG16. Tandel *et al*. [54], proposed a transfer learning based CNN model for brain tumor grading, demonstrating superior performance over six classical machine learning classifiers. They also developed five relevant multiclass MRI datasets ranging from two to six tumor classes.

Tandel *et al.* [55], curated four clinically relevant brain tumor datasets and evaluated them using five deep learning models and five machine learning models via five-fold cross-validation. To enhance classification accuracy, they proposed a majority voting ensemble algorithm, which effectively leveraged the strengths of all models. Emam *et al*. [56], introduced a metaheuristic optimizer that was applied to fine-tune the ResNet50 architecture, resulting in the I-HGS-ResNet50 model.

The analysis of recent advances shows that hybrid and ensemble models [57] are steadily reshaping the landscape of brain tumor research. By combining multiple architectures [58] and optimization strategies, these approaches achieve better accuracy and resilience with respect to single-model baselines [59]. Algorithms with meta-heuristic capabilities have emerged as efficient tools for fine-tuning deep learning frameworks, further boosting performance. Transfer learning continues to provide a strong foundation, though its success remains closely tied to preprocessing quality [60]. Despite these strengths, challenges such as dataset dependency, computational demands and limited interpretability persist across studies.

2. CONCLUSION AND FUTURE WORK

This work presents a wide-ranging review of recent advancements in AI driven brain tumor detection using MRI scans, focusing on technical methodologies, classification strategies and real-world challenges. By analyzing various tumor types and deep learning frameworks, it evaluates the clinical readiness, limitations and future potential of AI in transforming neuro-oncology. Covering highly influential studies, the review traces the evolution from traditional methodologies to advanced implementation models. Many powerful hybrid and ensemble approaches have been explored in tumor classification among those PSO–XGBoost stands out by combining PSO with gradient boosting. The CNN+SVM hybrid leverages deep CNNs for feature extraction with SVM classifiers, demonstrating effective in both binary and multi-class classification. Parallel dilated CNN (PDCNN) excels at capturing multi-scale features, achieving a strong balance across accuracy, precision and recall. I-HGS–ResNet50, optimized with the improved hunger games search algorithm, is a strong metaheuristic-tuned contender. Ensemble approaches like majority voting enhance robustness by combining predictions from multiple models. The EDCNN (VGG16+SCNN) integrates transfer learning with spatial attention through skip connections, offering nuanced classification capabilities. The transfer learning with ResNet50 remains consistent though preprocessing quality is critical, while earlier approaches such as GoogLeNet+traditional ML classifiers are less competitive in recent comparisons. The strength of these models lies in their ability to learn complex patterns, reducing reliance on manual interpretation and enabling earlier diagnoses. Techniques like Grad-CAM and architectures such as ResNet50 further boost interpretability and clinical confidence. However, clinical adoption still faces challenges like inter-patient variability, limited annotated data, overfitting and a lack of large-scale validation. Regulatory requirements and transparent AI behavior remain key hurdles. Future research should focus on developing models that generalize across patient diversity, integrating multi-modal data deploying interpretable AI techniques, optimizing models for real-time edge deployment and aligning deep learning systems with clinical standards to build trust in AI-assisted diagnostics.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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APPENDIX

Table 1. Architectures and classification of tumor

Ref	Architectures implemented	Results
[2]	Cascaded-ConvNet.	Dice similarity coefficient (DSC) scores of 0.9203 for whole tumors (WT), 0.9113 for enhancing tumors (ET), and 0.872 for tumor cores (TC).
[3]	3D CNN and a U-Net.	DSC of 0.750, 0.906 and 0.846 for ET, WT, and TC, respectively.
[5]	A joint learning-based feature reconstruction framework combined with an enhanced neural network architecture.	DSC of 86.28% for WT, 77.02% for TC and 59.64% for ET.
[6]	Spectral data augmentation-based deep autoencoder CNN.	Accuracy of 97% and an AUC ROC score of 99.46% for classifying tumor or no tumor.
[7]	LW-DNN was trained using a hybrid optimization strategy that combines the WOA with BWO.	Precision and recall are 98.12% and 96.30% respectively.
[10]	BTSCNet.	Accuracy obtained are 96.6% for Meningioma, 98.1% for glioma, and 95.3% for pituitary tumor
[13]	An ensemble deep learning framework that integrates four architectures ResNet50, VGG19, InceptionV3, and MobileNet.	Using the VGG19 architecture, the model achieved an accuracy of 99.85%. The area under the ROC curve (AUC) was calculated as 1.0 across all four categories normal, glioma tumor, meningioma tumor, and pituitary tumor.
[14]	HOG-SMP-SGD.	Precision is 97.1%, 96.3%, and 99.5% for meningioma, glioma, and pituitary tumors respectively.
[16]	Combination of WO and HHO.	The model achieved an 81.6% accuracy, 79.1% specificity of 0.791 and 97.4% sensitivity.

Table 1. Architectures and classification of tumor (*continued*)

[17]	RCNN with two channel CNN.	Avg. confidence score is 0.991 and 0.976 for meningioma and pituitary tumor.
[19]	Multimodal deep transfer learning.	DSC of meningioma, glioma and pituitary are 0.9459 0.7241 0.9108 respectively.
[22]	A Hyb-DCNN enhanced through nature-inspired ResNet-152 transfer learning.	Consistently outperformed existing benchmark models, achieving accuracies of 99.57%, 97.28%, 94.31%, 95.48%, 96.38%, 98.41%, and 96.34% across multiple evaluations and recorded lower error rates when compared against conventional methods.
[23]	Multimodal attention-gated cascaded U-Net model.	DSC for WT, TC, and ET 90.45, 84.3, and 82.16 respectively.
[24]	Fractional aquila spider monkey optimization based SqueezeNet.	In the classification of brain tumors across four grades the model attained a testing accuracy of 92.2%, with 94.3% sensitivity, and 90.8% specificity, while maintaining a prediction error of 0.089.
[25]	DBN-QLBC integrates deep belief networks with quadratic logit boosting.	MRI scans are classified into two categories: normal and abnormal.
[26]	Combination of PO and PSO alongside CNN.	Accuracy is 0.97, sensitivity is 0.98, and specificity is 0.96.
[29]	U-Net model with leaky ReLU.	U-Net architecture achieved dice scores of 0.928 for whole tumor, 0.854 for core tumor, and 0.792 for enhancing tumor, respectively.
[31]	Multiscale cascaded multitask network.	96.27 and 95.88 for DCS and mean IoU, respectively, 97.988 accuracy for classification of glioma, pituitary tumor, and meningioma.
[32]	Glioma brain tumor detection through dual CNN along with histogram density segmentation algorithm.	Sensitivity, specificity, and accuracy of 98.9, 99.04, and 98.85 respectively for high grade glioma (HGG) and sensitivity, specificity and accuracy of 98.67, 98.82, and 98.98 respectively for low grade glioma (LGG).
[34]	Exponential deer hunting optimization-based Shepard convolutional neural network (ExpDHO-based ShCNN).	Accuracy, sensitivity, and specificity of 0.929, 0.934, and 0.939 for brain tumor detection, respectively, of 0.917, 0.918, and 0.919 for brain tumor classification.
[35]	Gradient-assisted multi-category brain tumor segmentation method (GAM-Net).	DSC are 0.8991, 0.8402, and 0.7580 in WT, TC, and ET respectively.
[36]	Regression neural network along with optimized and relief-based feature reduction.	Accuracy (94.7%), sensitivity (94.78%), specificity (94.6%), precision (94.45%), F1-score (94.66%), error rate (10.5%) for classifying pituitary, meningioma, and glioma
[38]	Hybrid SCAOA.	Pituitary tumors, gliomas, and meningioma detection with accuracy of 93.0%, sensitivity of 92.3%, and specificity of 92.0%.
[39]	Self-attention progressive GAN combined with momentum search optimization.	Segments MRI images into tumor and non-tumor categories with accuracy of 99.97%.
[40]	Residual fused Shepherd convolution neural network.	Accuracy of 94%, sensitivity of 95% and specificity of 94.9%.
[41]	Hybrid AlexNet-GRU	Classifies pituitary, meningioma, glioma, and no Tumor with 97% accuracy, 97.63% precision, 96.78% recall rate, and 97.25% F1-score
[46]	Transfer learning and VGG16 architecture ‘‘23 layers CNN”.	Accuracies of 97.8% and 100% multiclass (meningioma, glioma, and pituitary) brain tumors and binary (normal and abnormal) respectively.
[49]	Template-driven K-means clustering approach that incorporates superpixels PCA.	Accuracy of 95.0%, sensitivity of 97.36%, and specificity of 100% for detecting different sizes of the tumors.
[50]	XGBoost approach.	97% accuracy, 97% specificity, 98% precision, and 98% recall for detecting brain tumor.
[52]	Modified GoogLeNet.	Precision of 94.7, 99.2, 98.0, recall of 96.0, 97.9, 98.9, and specificity of 98.4, 99.4, and 99.1 for meningioma, glioma, and pituitary tumor respectively.
[53]	CNN based U-Net andVGG.	DSC and tumor detection accuracy are 0.84 and 0.92, respectively.
[56]	Improved hunger games search algorithm (I-HGS-ResNet50).	Accuracy 99.89%, sensitivity 99.91%, specificity 99.94%, precision 99.87%, and F-score 99.92% (binary and multiclass).

Table 2. The contribution, training algorithm, datasets, and limitations of the most used segmentation and classification methods for detection of brain tumor

Ref	Techniques	Performance metrics	Dataset	Limitations
[1]	CNN, VGG-16, and Ensemble	Accuracy=96%, 98.15%, and 98.41% F1-score=91.78%, 92.6%, and 91.29% Recall=89.5%, 94.4%, and 91.4%	MRI dataset	Used only a single dataset.
[2]	C-ConvNet and DWA mechanism	HAUSDORFF99=1.427, dice similarity=0.9203, and sensitivity=0.9386	BRATS 2018	Increase in the size of the tumor decreases the feature extraction performance.
[3]	3D U-Net and CNN	Dice scores=0.750, 0.906, and 0.846	BraTS-19	Image processing is not applied to Ensemble.
[4]	Radiomics and TFCS	AUROC=0.833, accuracy=0.807, MCC=0.457, and AUPR=0.769	6 OA, 1 private	For the classification tasks, class imbalance is not considered.
[6]	SDA-DA CNN and Deep autoencoder	Accuracy=97% and AUC ROC=99.46	Kaggle	Recall score is not improved.
[7]	WOA and BWO	Accuracy=97%	BRATS	The model's performance cannot be judged using only Accuracy.

Table 2. The contribution, training algorithm, datasets, and limitations of the most used segmentation and classification methods for detection of brain tumor (*continued*)

[8]	DenseNet201	MAP=0.88, AUC=0.89, and DCG=0.26	BT-MRI	Limitations in smaller lesions or no tumors.
[9]	MCNN	Accuracy=0.96-0.99, recall=0.72-0.99, specificity=91.6-99.1, and precision=0.84-0.99	Brats 2015, Figshare	Few performance metrics can be improved.
[11]	Stacked LSTM and Bi-LSTM	Accuracy=98.85-99.23%, sensitivity=99.23-99.62%, and specificity=98.08-98.85%	INTERPRET database	Accuracy may be lower in binary classification of diffuse astrocytoma and pseudo brain tumors.
[14]	HOG, SVM, and SMP algorithms	Accuracy=97%	Cheng 2015	Accuracy alone cannot be used to judge the model's performance.
[17]	CNN and RCNN	Accuracy=98.21 execution time=277.174s	Figshare and Kaggle	Limited to object detection and segmentation not used.
[21]	GS-MVO-DBN	F1-score=0.95522 and accuracy=0.95238	Kaggle	Effective preprocessing could have been incorporated.
[26]	IPO, CNN, and particle swarm optimizer	Accuracy=97.09%	Br35H dataset	Complexity of the model.
[30]	HOG and modified ResNet50	Accuracy=88%	Kaggle	Issues in detection and categorization of tumors.
[32]	Dual CNN and HDSA	Sensitivity=98.9%, specificity=99.04%, and accuracy=98.85%	BraTS-IXI dataset	Diagnosing procedure and time consumption for tumor detection not included.
[33]	JGate-AttResUNet	Dice=0.8960, 0.9131, sensitivity=0.8734, 0.8421, and accuracy=0.9499, 0.9369	Brats 2015, 2019	For smaller objects with substantial shape diversity, the false-positive predictions.
[40]	RFShCNN	Accuracy=94%, sensitivity=95%, and specificity=94.9%.	Brats, Figshare	Big data requirement of annotated images, also it is a time-consuming process.
[41]	AlexNet-GRU	Accuracy=97%, precision=97.63%, recall rate=96.78%, and F1-score=97.25%	Kaggle	High-quality, diverse, and annotated datasets were not considered.
[49]	Template-based K-means (TK) algorithm	Accuracy=95.0%, sensitivity=97.36%, specificity=100%, and execution time=35-60s	Kaggle, OA, and Local dataset	Implemented on small dataset
[56]	I-HGS, (ResNet50)	Accuracy=99.72-99.89%	Cheng Dataset, BT-large-4c, and BT-large-2c	Tends to become confined within local regions and struggles to maintain an effective exploration–exploitation balance, particularly in complex, high-dimensional problems.

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