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Review on Hybrid Deep Learning Approaches for Early Detection and Segmentation of Brain Tumors from MRI Images Using the BraTS Dataset

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Abstract **-** Brain tumors require accurate and timely detection and segmentation to support effective diagnosis and treatment planning. Magnetic Resonance Imaging (MRI) provides valuable multimodal information, but manual analysis is time-consuming and challenging because of tumor heterogeneity, irregular morphology, and unclear tumor boundaries. This review aims to examine hybrid deep learning approaches for automated brain tumor detection and segmentation, with particular emphasis on the BraTS dataset. The reviewed studies are analyzed according to their architectural strategies, datasets, evaluation metrics, and reported performance, covering CNN-based, U-Net-based, CNN–Transformer, attention-based, 3D, optimization-based, and multimodal approaches. The findings indicate that hybrid architectures can effectively combine local spatial, global contextual, volumetric, and multimodal features to improve tumor detection and segmentation. Reported studies achieved promising performance, including 98.4% accuracy and 96.8% sensitivity, Dice scores of up to 0.975, and classification accuracy of 98.78%. However, important challenges remain, including limited annotated data, class imbalance, computational complexity, poor cross-dataset generalization, limited interpretability, and insufficient clinical validation. Future research should focus on integrated detection and segmentation, robust multimodal fusion, efficient CNN–Transformer models, semi-supervised learning, explainable AI, and multi-center clinical validation. Overall, hybrid deep learning demonstrates strong potential for accurate, robust, and clinically applicable MRI-based brain tumor analysis.

Keyword: *Brain Tumor, MRI, Deep Learning, Hybrid Deep Learning, Brain Tumor Segmentation, BraTS, CNN, U-Net, Transformer, Medical Image Analysis.*

1. Introduction

Brain Tumors are a very complex neurological disorder that should be detected, localized and segmented precisely for diagnosis and treatment planning. MRI is well-used due to its detailed,

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multimodal, and anatomical information. Manual interpretation of MRI images, however, can be time consuming and is subject to variation in tumor size and shape, difficult margins, image quality, and inter-observer interpretation [1].

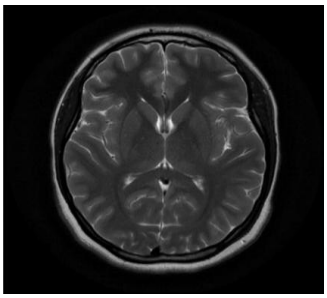


Fig 1 Normal brain MRI image[2]

Thanks to the recent progress in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL), automated brain tumor analysis is now possible [3]. The CNNs, U-Nets, encoder–decoder networks, attention mechanisms and Transformers can be trained directly from MRI images to learn complex spatial and contextual features. These complementary capabilities can be integrated in hybrid models which can further enhance tumor detection and segmentation[4].

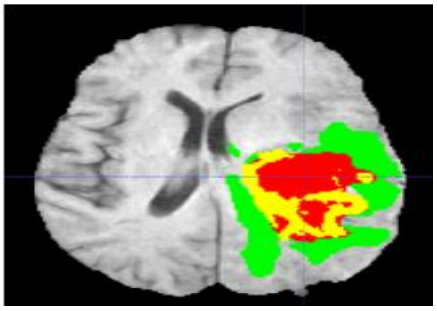


Fig 2 Brain tumor MRI with segmentation[5]

BraTS is a significant dataset for assessing the accuracy of brain tumor segmentation algorithms, as it includes multimodal MRI data (T1, T1ce, T2, FLAIR) and manually labeled areas of tumor. However, there are still unmet needs such as MRI heterogeneity, lack of annotated data, class imbalance, computational complexity, lack of cross-dataset generalization and limited model interpretability[6].

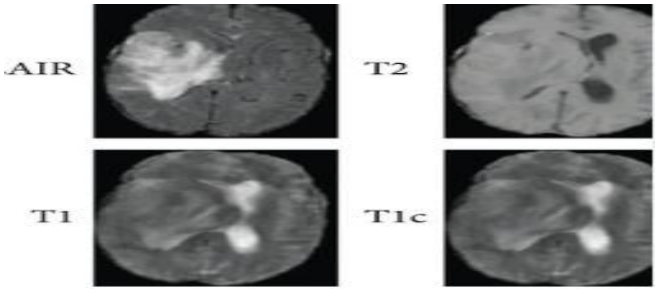


Fig 3 Multimodal MRI sequences used in the BraTS dataset for brain tumor analysis[7]

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This review aims to focus on the hybrid deep learning techniques used for MRI-based brain tumor detection and segmentation like CNN–U-Net, attention-based, CNN–Transformer, 3D, optimization-based, and multimodal methods. It summarizes their methodologies, datasets, evaluation metrics and reported performances and exposes research gaps and directions for accurate, robust, explainable, and clinically applicable brain tumor analysis systems[8].

II. Literature Review

Muthulakshmi & Jayalakshmi, 2026[9] they proposed U-Net with KPFRFCM and PSO which segments very well and is robust to noise as they have gone with advanced preprocessing, optimization, clustering and cross validation

Devi et al., 2026 [10] using channel-spatial attention and they achieved better Dice score and better segmentation of whole, core and enhancing tumor region.

Aslan & Özüpak, 2026[8] which successfully extracted features with a deep network and achieved precise localization and robust performance with Dice, IoU, and AUC scores.

Sakhare, 2026 [6] proposed a spatio-temporal learning and attention based Hybrid ResNet3D-LSTM, Transformer, FPN-UNet for efficient brain tumor detection and segmentation.

Saifullah et al., 2026 [4] Proposed PSO-GA-U-Net, which uses metaheuristic algorithms for learning rate and dropout optimization, and obtained good segmentation accuracy and performance on various datasets.

TABLE. I LITERATURE SUMMARY

Author/Year	Method	Dataset	Results	Research Gap
Nogair et al. (2026) [3]	Reviewed CNN, U-Net, attention, residual, and hybrid models.	BraTS, TCIA	Highlighted effective segmentation and classification approaches.	Limited generalization, interpretability, and clinical validation.
Shivahare et al. (2026) [1]	MultiAttenNet combining CNN, Transformer, and semi-supervised learning.	BraTS 2023, Figshare	Achieved 98.4% accuracy and 96.8% sensitivity.	Requires broader clinical validation and better generalization.

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Masooma et al. (2026) [11]	Hybrid VGG16–ResNet50 for tumor detection.	MRI, PET, medical imaging	Achieved 80% overall accuracy.	Limited segmentation, dataset details, and external validation.
Prabhas et al. (2025) [12]	Ensemble CNN and transfer learning using MobileNetV2, ViT, and VGG16.	Brain MRI dataset	VGG16 achieved highest accuracy of 98.78%.	Focuses on classification, lacking localization and segmentation.
Yeafi et al. (2025) [13]	3D DSNet with adversarial learning, DCNN, and attention.	BraTS 2018–2020	Achieved Dice scores up to 0.975.	Requires improved efficiency, explainability, and clinical validation.

The reviewed studies show good advancements in hybrid CNN, Transformer, attention-based, 3D, and optimization-driven techniques in brain tumor analysis. Most of the existing studies focus on classification/detection or segmentation tasks but not on a combined framework for early detection and exact segmentation of the object [14]. Besides, the problems of multimodal MRI fusion, class imbalance, cross-dataset generalization, interpretability, annotation dependency, computational efficiency, and clinical validation are still open [15]. These gaps inspire further research on a hybrid deep learning system for brain tumor detection and segmentation in the first stage, with the aim of achieving a comprehensive and accurate identification of the tumor[16].

III. Hybrid Deep Learning Techniques for Brain Tumor Detection and Segmentation

By integrating complementary architectures, hybrid deep learning is able to learn multiple MRI modalities, contexts, structures, and spatial features. Common combinations include CNNs, U-Net, attention, Transformers, 3D networks, recurrent networks, and optimization techniques, all of which enhance the performance in tumor detection, localization, and segmentation [17].

A. CNN-Based Hybrid Models

CNNs are commonly used in brain tumor analysis due to the ability of extracting spatial and textural features from the MRI images. The hybrid CNN models include the architectures of VGG, ResNet, DenseNet, Res2Net, EfficientNet, and MobileNet to extract complementary multi-level and multi-scale features. These models learn a wide range of tumor properties and fine-tune the tumor boundaries to enhance the detection, classification, and segmentation of

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tumors. While they can handle some of these issues, they may still struggle with the complexities of computation, the amount of training data needed and their lack of capacity to understand long-range contextual relationships[18].

B. U-Net-Based Hybrid Models

Brain tumor segmentation uses widely-used U-Net-based architectures, featuring an encoder–decoder network with skip connections, which ensure high-quality retention of fine spatial details. The hybrid variants feature heterogeneous modules including encoders like ResNet, Res2Net, VGG, and Dense Net, attention, fuzzy clustering, optimization and multi-scale feature extraction.

These combinations are used to enhance feature representation and localization of diagnostically relevant areas, which supports the segmentation of whole tumor, tumor core and enhancing tumor regions. On the other hand, they might not be as effective depending on tumor morphology, MRI modality, dataset properties, and segmentation target and they could also be more demanding in terms of computation requirements, especially for more complex structures[19].

C. CNN–Transformer Hybrid Models

To supplement local spatial features learned by CNNs, Transformers are gaining popularity in medical image analysis tasks, which are better suited to extracting long-range dependencies and global information from images. Medical image analysis tasks are also increasingly becoming more suitable for Transformer networks due to their ability to capture long-range dependencies and global contextual information, complementing the local spatial features learned by CNNs[20]

CNN–Transformer hybrid models typically rely on the CNN layers or CNN-based encoders to capture the local features while the Transformer modules are used to learn the wider context relationship [21]. The representations that are generated can then be incorporated into classification or segmentation systems. The combination can be useful in brain MRI analysis in case of tumors of irregular shapes with heterogeneous intensity distribution and variable spatial distribution[22].

But the computational resources, memory and training data needed for Transformer-based models might be higher. The efficient architecture design and appropriate pretraining are thus essential for clinical application[23].

D. Attention-Based Hybrid Models

Attention mechanisms enhance hybrid deep learning models by highlighting salient spatial areas, feature channels, and tumor features. They can enhance tumor segmentation in small and ill-defined tumor regions in brain tumor segmentation[24].

Spatial attention, channel attention or combined attention are widely used in CNN + U-Net models. Spatial attention marks image locations that are salient, channel attention boosts representations of the features that are informative [25].

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Contextual feature learning can also be improved by incorporating attention into Transformer architectures, multi-scale CNNs, and encoder–decoder architectures. These modules can add to the complexity of computing, though, and attention maps should not be understood as definitive clinical explanations without proper validation of the maps[26].

E. 3D and Spatio-Temporal Hybrid Models

Brain MRI is inherently 3D and slice-wise 2D analysis might miss the context between the adjacent slices. 3D deep learning models, however, overlook this by analyzing the volumetric MRI data and learning the spatial relationships over multiple dimensions [27].

Hybrid 3D models combine 3D CNNs with U-Net, Transformers, attention, recurrent networks, or multi-scale modules to capture volumetric tumor characteristics and relationships across slices[28].

However, higher computational resources, memory, and standardized volumetric preprocessing are required for the use of 3D and spatio-temporal models, possibly restricting the practical use of these models[29].

F. Optimization-Based Hybrid Models

To optimize the configuration of the model, feature selection, and parameter tuning, hybrid methods based on deep learning are integrated with other methods, like Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and fuzzy clustering [30].

uch techniques may be used to maximize learning rates, network parameters, dropouts, and segmentation. Fuzzy clustering is also used to deal with uncertainty and intensity changes in MRI images [31].

While these can enhance model accuracy and generalization, they can also be time-consuming and complex, especially depending on the optimization technique and the nature of the data[32].

G. Multimodal MRI-Based Hybrid Models

Multimodal MRI involves sequences including T1, T1 with contrast, T2, and FLAIR, which all provide complementary information about the characteristics of brain tissue and/or tumors. These modalities can be used together to enhance tumor representation. In hybrid multimodal models, features are fused across modalities at the early, intermediate, late or attention stage. CNNs, Transformers, and encoder–decoder networks can be used to improve feature learning and segmentation[33].

The reliability of models can be compromised by the omission of modalities; by differences in acquisition such as different time intervals or number of scans; by differences in intensity; and by differences in image quality. Therefore there is a need for robust fusion methods to heterogeneous and incomplete MRI data [34].

IV. Comparative Analysis and Research Gaps

As revealed in the reviewed literature, there has been significant progress in the area of hybrid deep learning techniques for brain tumor detection, classification, and segmentation. Some

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architectures have been proposed to overcome the problems of traditional CNN and segmentation model. CNN-based hybrids mainly rely on extracting discriminative local features, while U-Net based approaches highlight the accurate spatial reconstruction and tumor-boundary delineation. CNN–Transformer architectures learn features by also considering the global context, while attention-based models are better at focusing on the diagnostically relevant features. Three dimensional approaches take advantage of volume information, while optimization-based models try to optimize the parameters of the model and generalization. Multimodal approaches further take advantage of complementary information available from other MRI sequences[35].

A. Comparison of Datasets

BraTS is one of the most popular stand-alone data for brain tumor segmentation, and other collections like TCIA and Figshare offer more MRI data. Comparisons may be difficult because of differences in patient populations, imaging protocols, preprocessing, and annotations. Hence, cross-dataset and external validation is important to evaluate the model robustness and generalizability[36].

B. Comparison of Detection, Classification, and Segmentation Capabilities

The previous studies discuss various stages of the analysis of brain tumors. Classification and detection help determine the presence of a tumor or type, segmentation determines the location and boundaries of a tumor[37].

The high classification accuracy does not necessarily translate into precise localization and good segmentation does not necessarily translate into early detection of tumor. So, a combination of detection, classification and accurate segmentation would be required for comprehensive MRI based tumor analysis [38].

C. Comparison of Hybrid Architectures

CNNs are effective local features extractors and U-Net is a good spatial reconstruction for segmentation. Transformers gain the ability to model the world, but need more resources. Attention mechanisms better select features, while 3D models better capture the volume. Optimization-based techniques improve parameter optimization, but can be more complex. In general, none of these approaches solves all the problems, and task specific non-redundant hybrid architectures are required for the problems to be solved efficiently[39].

D. Comparison of Evaluation Measures

For the detection and segmentation of brain tumors, various accuracy metrics such as the accuracy, precision, recall, sensitivity, specificity, f1 score, dice similarity coefficient (dsc), io-u, and jaccard index are commonly used to assess the models. Dice and IoU are important attributes when measuring segmentation overlap especially in the context of measuring the success of segmentation. Whole tumor, tumor core and enhancing tumor evaluations are recommended as region-wise assessments of the overall class imbalance can affect overall

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accuracy. The reliability in model evaluation is further enhanced by cross validation, external testing, statistical analysis and visual assessmen [40].

E. Limitations of Existing Approaches

The reviewed studies have several limitations, such as strong reliance on the benchmark dataset and few studies have been able to make cross-dataset generalizations because of MRI and patient variability. Manual annotation is tedious and difficult for small and vague tumor regions. High computational resources are also needed for Complex 3D and Transformer-based models. Furthermore, such systems are limited in interpretability, lacking in real-world clinical testing, and need to be validated in the future in multiple centers [41].

F. Key Research Gaps

Based on the comparative analysis, the major research gaps can be summarized as follows:
Additionally, there are some challenges in current research related to brain tumor analysis such as limited integration of detection with precise segmentation, inconsistent multimodal MRI fusion and limited cross-dataset generalization. MRI variability and class imbalance further hinder accurate segmentation of small, irregular and poorly-defined tumor regions. Also, some complex hybrid models are too costly computationally and lack interpretability. Most studies use data from retrospective benchmark sets, which underscore the importance of independent, multi-center, prospective clinical validation and more accurate and complete detection of small and/or early lesions.

V. Challenges in Hybrid Deep Learning-Based Brain Tumor Analysis

There are several challenges for brain tumor analysis using hybrid deep learning, such as the heterogeneity of MRI data, the variability of tumors, the multimodal fusion, the limited size of data sets annotated by tumor types, and class imbalance [42].

High computational resources are needed for complex CNN-Transformer and 3D models, too. In addition, low generalization ability across datasets, lack of interpretability, non-uniform preprocessing and lack of reproducibility limit reliable comparisons. Many also need comprehensive external and field validation prior to the use in practice[43].

VI. Future Research Directions

Multi-modal MRI fusion and CNN–Transformer architectures for the fusion of local and global features should be explored in future work.Future studies could focus on how to integrate detection and segmentation, effective multimodal MRI fusion, and CNN–Transformer architectures for fusion of local and global features. To meet clinical needs, lightweight models are required to reduce the computational requirements. Explainable AI can help make systems more transparent and trustworthy, and semi-supervised learning can help minimize the need for labeled data. In addition, good cross-dataset generalization is required and multi-center, real-world clinical validation is necessary for practical deployment.

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VII. Conclusion

In this review, the development of hybrid deep-learning methods for brain tumor detection and segmentation in MRI was focused, specifically around the BraTS benchmark. The potential of combining complementary learning capabilities for enhanced tumour analysis is clearly illustrated by CNN-based, U-Net-based, Transformer, attention, 3D, optimization-based and multimodal approaches. But there are some difficulties as well, such as MRI heterogeneity, limited annotated data, class imbalance, computational complexity, cross-dataset generalization, interpretability, and lack of clinical validation.

The literature also suggests the requirement for unifying frameworks that can handle the early detection of tumors and tumor accurate segmentation in the same framework, instead of solving them separately. Robust multimodal fusion, efficient CNN–Transformer architectures, semi-supervised learning, explainable AI, domain generalization, and multi-center validation should be a focus of future research. Overall, deep learning in the hybrid approach offers great promise for automated and clinically useful analysis of brain tumors, but further studies are needed before a reliable deployment in clinical use.

VI. References

[1] B. D. Shivahare, S. K. Subramaniam, Dafik, S. R, S. S. K. B, and S. S. S, "An advanced hybrid deep learning framework for high-precision brain tumor detection and classification in MRI scans," *Sci. Rep.*, vol. 16, no. 1, 2026, doi: 10.1038/s41598-026-50194-x.

[2] F. Gaillard, "Normal brain (MRI)," *Radiopaedia.org*, Jul. 2015, doi: 10.53347/RID-37605.

[3] N. A. Nogair *et al.*, "Deep Learning for Glioblastoma MRI Segmentation and Classification: A Structured Review of CNN-Based and Hybrid Architectures," *IEEE Access*, vol. 14, no. June, 2026, doi: 10.1109/ACCESS.2026.3692612.

[4] S. Saifullah, R. Dreżewski, A. Yudhana, R. Tanone, and A. P. Suryotomo, "A Hybrid Particle Swarm–Genetic Algorithm Framework for U-Net Hyperparameter Optimization in High-Precision Brain Tumor MRI Segmentation," *Appl. Sci.*, vol. 16, no. 6, pp. 1–46, 2026, doi: 10.3390/app16063041.

[5] A. Myronenko, "3D MRI brain tumor segmentation using autoencoder regularization," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 11384 LNCS, pp. 311–320, 2019, doi: 10.1007/978-3-030-11726-9_28.

[6] S. V. Sakhare, "An Iterative and Analytical Hybrid Deep Learning Framework for Enhanced Brain Tumor Detection and Segmentation in MRI Video Scans," *MEJ Mansoura Eng. J.*, vol. 51, no. 3, 2026, doi: 10.58491/2735-4202.3468.

[7] "A selection of pictures from the Multimodal Brain Dataset (BraTS) [17]. | Download Scientific Diagram." Accessed: Aug. 31, 2026. [Online]. Available: https://www.researchgate.net/figure/A-selection-of-pictures-from-the-Multimodal-Brain-

Dataset-BraTS-17_fig4_362798067

[8] E. Aslan and Y. Özüpak, "A hybrid deep learning framework based on VGG19 and U-Net for accurate brain tumor segmentation in MRI images," *Magn. Reson. Lett.*, vol. 6, p. 200275, 2026, doi: 10.1016/j.mrl.2026.200275.

[9] K. Muthulakshmi and M. Jayalakshmi, "Deep approach of brain tumor classification: A hybrid model," *Array*, vol. 31, no. August, p. 101132, 2026, doi: 10.1016/j.array.2026.101132.

[10] C. N. Devi, T. S. Lawrence, and P. R. Subramaniam, "A novel hybrid Res2Net-UNet model for accurate brain tumor segmentation in MRI," *Int. J. Cogn. Comput. Eng.*, vol. 7, no. 1, pp. 310–324, 2026, doi: 10.1016/j.ijcce.2025.11.005.

[11] U. Masooma, J. U. Arshed, N. Ambreen, M. Afzal, M. A. Qureshi, and S. Yousaf, "Hybrid Deep Learning for Brain Tumor Detection Using Multi-Modal Scans," *VFAST Trans. Softw. Eng.*, vol. 14, no. 2, pp. 465–479, 2026, doi: 10.21015/vtse.v14i2.2423.

[12] K. S. Prabhas *et al.*, "A Deep learning framework for brain tumor detection using CNNs and transfer learning on MRI scans," *Syst. Soft Comput.*, vol. 7, no. September, p. 200389, 2025, doi: 10.1016/j.sasc.2025.200389.

[13] A. Yeafi, M. Islam, and M. S. U. Yusuf, "A deep learning framework for 3D brain tumor segmentation and survival prediction," *Healthc. Anal.*, vol. 8, no. September, p. 100418, 2025, doi: 10.1016/j.health.2025.100418.

[14] S. Panigrahi, D. R. Das Adhikary, and B. K. Pattanayak, "Hybrid transfer learning and self-attention framework for robust MRI-based brain tumor classification," *Sci. Rep.*, vol. 15, no. 1, pp. 1–30, 2025, doi: 10.1038/s41598-025-09311-5.

[15] R. Missaoui, W. Hechkel, W. Saadaoui, A. Helali, and M. Leo, "Advanced Deep Learning and Machine Learning Techniques for MRI Brain Tumor Analysis: A Review," *Sensors*, vol. 25, no. 9, pp. 1–38, 2025, doi: 10.3390/s25092746.

[16] R. Salakapuri, P. V. Terlapu, K. R. Kalidindi, R. N. Balaka, D. Jayaram, and T. Ravikumar, "Intelligent brain tumor detection using hybrid finetuned deep transfer features and ensemble machine learning algorithms," *Sci. Rep.*, vol. 15, no. 1, pp. 1–27, 2025, doi: 10.1038/s41598-025-08689-6.

[17] K. Gencer and G. Gencer, "Hybrid deep learning approach for brain tumor classification using EfficientNetB0 and novel quantum genetic algorithm," *PeerJ Comput. Sci.*, vol. 11, pp. 1–26, 2025, doi: 10.7717/PEERJ-CS.2556.

[18] N. Netshamutshedzi, R. Netshikweta, J. C. Ndogmo, and I. C. Obagbuwa, "A systematic review of the hybrid machine learning models for brain tumour segmentation and detection in medical images," *Front. Artif. Intell.*, vol. 8, no. September, pp. 1–11, 2025, doi: 10.3389/frai.2025.1615550.

[19] A. Belhadi, Y. Djenouri, and A. N. Belbachir, "Ensemble fuzzy deep learning for brain

tumor detection," *Sci. Rep.*, vol. 15, no. 1, 2025, doi: 10.1038/s41598-025-90572-5.

[20] F. Alshomrani, "Challenges and Advances in Classifying Brain Tumors: An Overview of Machine, Deep Learning, and Hybrid Approaches with Future Perspectives in Medical Imaging," *Curr. Med. Imaging Former. Curr. Med. Imaging Rev.*, vol. 21, pp. 1–19, 2025, doi: 10.2174/0115734056365191250602124819.

[21] R. Disci, F. Gurcan, and A. Soylu, "Advanced Brain Tumor Classification in MR Images Using Transfer Learning and Pre-Trained Deep CNN Models," *Cancers (Basel).*, vol. 17, no. 1, pp. 1–21, 2025, doi: 10.3390/cancers17010121.

[22] G. Eleyan, Z. Al-Barakeh, R. Ghandour, B. Neji, and A. Eleyan, "Brain Tumor Detection Via Ensemble CNN-Based Deep Learning Models," *Proc. - 6th Int. Conf. Bio-Engineering Smart Technol. BioSMART 2025*, pp. 1–4, 2025, doi: 10.1109/BioSMART66413.2025.11046093.

[23] N. Rasool and J. I. Bhat, *Brain tumour detection using machine and deep learning: a systematic review*, vol. 84, no. 13. Springer US, 2025. doi: 10.1007/s11042-024-19333-2.

[24] K. Chiranjeevi and D. Victosudhageorge, "Brain tumor detection and classification using deep learning algorithms: A survey," *AIP Conf. Proc.*, vol. 3162, no. 1, pp. 1–19, 2025, doi: 10.1063/5.0241733.

[25] E. Gundogan, "A Novel Hybrid Deep Learning Model Enhanced with Explainable AI for Brain Tumor Multi-Classification from MRI Images," *Appl. Sci.*, vol. 15, no. 10, 2025, doi: 10.3390/app15105412.

[26] S. Bouhafra and H. El Bahi, "Deep Learning Approaches for Brain Tumor Detection and Classification Using MRI Images (2020 to 2024): A Systematic Review," *J. Imaging Informatics Med.*, vol. 38, no. 3, pp. 1403–1433, 2025, doi: 10.1007/s10278-024-01283-8.

[27] M. Thahiruddin and A. Wulandari, "CNNs vs. Hybrid Transformers for Brain Tumor Classification on the BRISC Dataset," *J. Apl. Teknol. Inf. dan Manaj.*, vol. 6, no. 1, pp. 24–33, 2025, doi: 10.31102/jatim.v6i1.3545.

[28] R. Haque, M. M. Hassan, A. K. Bairagi, and S. M. Shariful Islam, "NeuroNet19: an explainable deep neural network model for the classification of brain tumors using magnetic resonance imaging data," *Sci. Rep.*, vol. 14, no. 1, pp. 1–22, 2024, doi: 10.1038/s41598-024-51867-1.

[29] I. Pacal, "A novel Swin transformer approach utilizing residual multi-layer perceptron for diagnosing brain tumors in MRI images," *Int. J. Mach. Learn. Cybern.*, vol. 15, no. 9, pp. 3579–3597, 2024, doi: 10.1007/s13042-024-02110-w.

[30] A. M. J. Zubair Rahman *et al.*, "Advanced AI-driven approach for enhanced brain tumor detection from MRI images utilizing EfficientNetB2 with equalization and homomorphic filtering," *BMC Med. Inform. Decis. Mak.*, vol. 24, no. 1, pp. 1–19, 2024, doi: 10.1186/s12911-024-02519-x.

[31] I. Pacal, O. Celik, B. Bayram, and A. Cunha, "Enhancing EfficientNetv2 with global and efficient channel attention mechanisms for accurate MRI-Based brain tumor classification," *Cluster Comput.*, vol. 27, no. 8, pp. 11187–11212, 2024, doi: 10.1007/s10586-024-04532-1.

[32] F. Ullah, M. Nadeem, and M. Abrar, "Revolutionizing Brain Tumor Segmentation in MRI with Dynamic Fusion of Handcrafted Features and Global Pathway-based Deep Learning," *KSII Trans. Internet Inf. Syst.*, vol. 18, no. 1, pp. 105–125, 2024, doi: 10.3837/tiis.2024.01.007.

[33] A. C. Buchade and M. P. Kantipudi, "Recent Trends on Brain Tumor Detection Using Hybrid Deep Learning Methods," *Rev. d'Intelligence Artif.*, vol. 38, no. 1, pp. 103–113, 2024, doi: 10.18280/ria.380111.

[34] A. H. Saleh, Ü. Atila, and O. Menemencioğlu, "Multimodal Fusion for Enhanced Semantic Segmentation in Brain Tumor Imaging: Integrating Deep Learning and Guided Filtering Via Advanced 3D Semantic Segmentation Architectures," *Int. J. Imaging Syst. Technol.*, vol. 34, no. 5, 2024, doi: 10.1002/ima.23152.

[35] S. M. Alqhtani *et al.*, "Improved Brain Tumor Segmentation and Classification in Brain MRI With FCM-SVM: A Diagnostic Approach," *IEEE Access*, vol. 12, no. May, pp. 61312–61335, 2024, doi: 10.1109/ACCESS.2024.3394541.

[36] A. K. Sahoo, P. Parida, and K. Muralibabu, "Hybrid deep neural network with clustering algorithms for effective gliomas segmentation," *Int. J. Syst. Assur. Eng. Manag.*, vol. 15, no. 3, pp. 964–980, 2024, doi: 10.1007/s13198-023-02183-w.

[37] M. A. Talukder *et al.*, "An efficient deep learning model to categorize brain tumor using reconstruction and fine-tuning," *Expert Syst. Appl.*, vol. 230, no. May, 2023, doi: 10.1016/j.eswa.2023.120534.

[38] J. Kataria and S. P. Panda, "HybridCSF model for magnetic resonance image based brain tumor segmentation," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 35, no. 3, pp. 1845–1852, 2024, doi: 10.11591/ijeecs.v35.i3.pp1845-1852.

[39] Chandni, M. Sachdeva, and A. K. S. Kushwaha, "IRNetv: A deep learning framework for automated brain tumor diagnosis," *Biomed. Signal Process. Control*, vol. 87, pp. 188–202, 2024, doi: 10.1016/j.bspc.2023.105459.

[40] S. Iqbal, A. N. Qureshi, M. Alhussein, K. Aurangzeb, I. A. Choudhry, and M. S. Anwar, "Hybrid deep spatial and statistical feature fusion for accurate MRI brain tumor classification," *Front. Comput. Neurosci.* , vol. 18, no. 1973, 2024, doi: 10.3389/fncom.2024.1423051.

[41] Z. U. Abidin, R. A. Naqvi, A. Haider, H. S. Kim, D. Jeong, and S. W. Lee, "Recent deep learning-based brain tumor segmentation models using multi-modality magnetic resonance imaging: a prospective survey," *Front. Bioeng. Biotechnol.*, vol. 12, no. July, 2024, doi:

10.3389/fbioe.2024.1392807.

[42] S. Suryawanshi and S. B. Patil, "Efficient Brain Tumor Classification with a Hybrid CNN-SVM Approach in MRI," *J. Adv. Inf. Technol.*, vol. 15, no. 3, pp. 340–354, 2024, doi: 10.12720/jait.15.3.340-354.

[43] M. M. Zahoor *et al.*, "Brain Tumor MRI Classification Using a Novel Deep Residual and Regional CNN," *Biomedicines*, vol. 12, no. 7, pp. 1–19, 2024, doi: 10.3390/biomedicines12071395.