Int. J. Adv. Res. Sci. Technol. Volume 13, Issue 6, 2024, pp. 2223-2227.

IJARST

International Journal of Advanced Research in Science and Technology

https://doi.org/10.62226/ijarst20262735

ISSN 2319 – 1783 (Print)

ISSN 2320 – 1126 (Online)

A Comprehensive Review of Brain Tumor Detection Using Advanced Machine Learning and Deep Learning Methods

[1]Palvadi Srinivas Kumar [2] Dr. Rajesh Kumar

[1]Research Scholar, Department of Computer Science and Engineering, University of Allahabad, Prayagraj, Uttar Pradesh – 211002, India

[2]Assistant Professor, Department of Electronics & Communication, University of Allahabad, Prayagraj, Uttar Pradesh - 211002, India

ARTICLE INFO

Article history:

Received	08 June 2024
Accepted	16 June 2024
Available online	20 June 2024

Keywords:

Segmentation, Feature Extraction, Validation, Disease

Indexed in:

Crossref

INDEX COPERNICUS INTERNATIONAL

Google scholar

and in major libraries

ABSTRACT

Accurate cancer identification is essential for therapy selection, treatment monitoring, and prognostic evaluation. Convolutional Neural Networks (CNNs are widely employed in medical image analysis due to their ability to automatically extract hierarchical features through convolutional and pooling operations. Extreme Learning Machines (ELMs), characterized by fast training and single hidden-layer architectures, have demonstrated effectiveness in classification and regression tasks. Gliomas, the most common and aggressive primary brain tumors, significantly affect patient survival, emphasizing the need for precise treatment planning. Magnetic Resonance Imaging (MRI) is the primary imaging modality for brain tumor diagnosis; however, the high dimensionality and large volume of MRI data limit the efficiency of conventional manual analysis. Therefore, reliable and automated tumor segmentation and classification techniques are critical for improving diagnostic accuracy and clinical decision-making.

I. Introduction

Training a radiologist requires substantial time and financial investment, and even experienced professionals face challenges in efficiently analyzing large-scale medical imaging data. The rapid advancement of Artificial Intelligence (AI) has the potential to significantly transform the medical domain, ranging from drug development to clinical decision support. Recent successes of AI algorithms in computer vision closely align with the growing digitization of healthcare systems. In the United States, Electronic Health Record (EHR) adoption increased markedly between 2007 and 2012, with clinical images forming a major component of patient records. Although medical images are traditionally interpreted by radiologists, human expertise is constrained by factors such as workload, fatigue, and variability in experience. Delayed or inaccurate diagnoses can adversely affect patient outcomes. Consequently, automated, accurate, and efficient AI-based medical image analysis systems are essential to enhance diagnostic reliability and optimize healthcare delivery.

The utilization of medical imaging modalities has increased substantially, driven by advancements in imaging technologies and their growing role in clinical diagnosis. A large-scale study conducted across six integrated healthcare systems in the United States analyzed imaging data collected between 1996 and 2010, encompassing approximately 30.9 trillion imaging examinations. The study reported utilization increases of 7.8% for computed tomography (CT), 10% for X-ray imaging, and 57% for positron emission tomography (PET) during the observation period. Early artificial intelligence paradigms in the 1970s led to the development of rule-based expert systems, with MYCIN serving as a notable example for antibiotic treatment recommendation. In parallel with these developments, AI methodologies evolved from traditional rule-based approaches to feature-based learning and supervised training frameworks. Although unsupervised learning techniques have gained attention, the majority of AI models reported between 2015 and 2017 predominantly relied on supervised learning strategies.

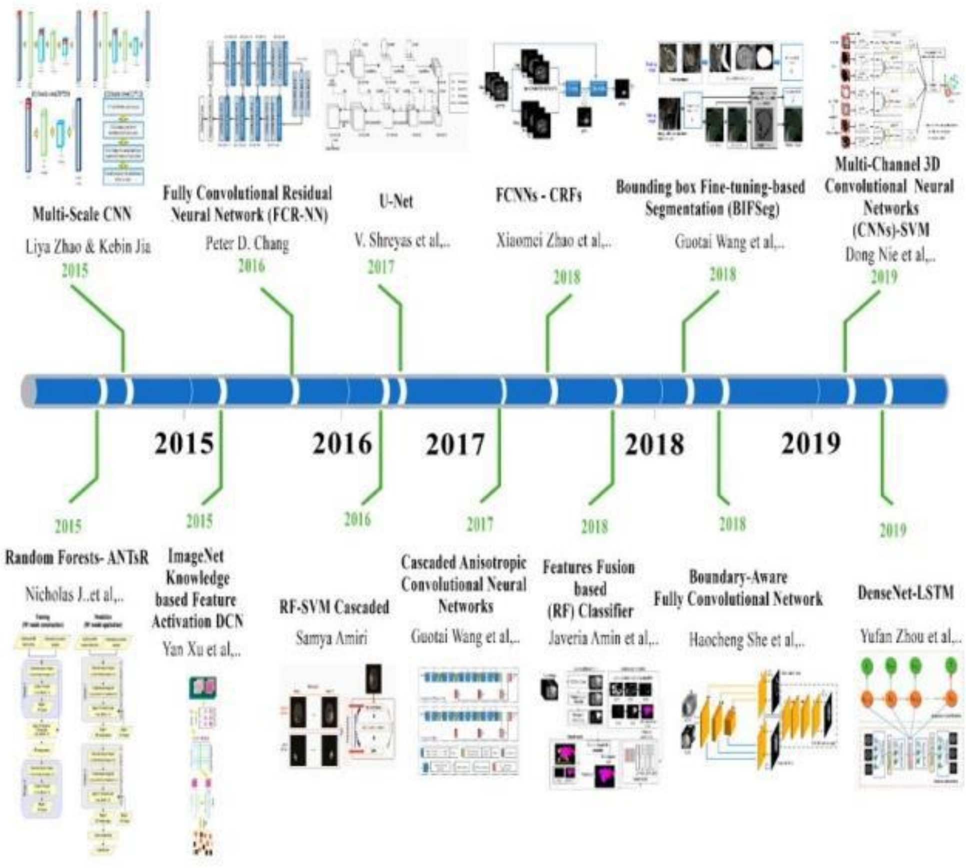

Figure 1: Development of Brain tumor using Machine Learning

II. Research Gap

Existing literature on brain tumor detection typically evaluates machine learning algorithms, deep learning architectures, or image segmentation frameworks in isolation. Consequently, current reviews often miss a holistic perspective that bridges conventional machine learning, advanced deep neural networks, hybrid pipelines, preprocessing paradigms, standardized datasets, and standard evaluation metrics—alongside emerging trends like Explainable AI (XAI) and Federated Learning (FL). Additionally, critical operational hurdles such as domain adaptation, multi-modal MRI integration, and real-world clinical integration remain underexplored.

To bridge these gaps, this review delivers a structured taxonomy of brain tumor diagnostic models, a rigorous side-by-side methodology evaluation, a detailed breakdown of benchmark datasets and performance measures, and a roadmap of open challenges and future research pathways designed to assist both AI researchers and clinical practitioners.

III. Literature Work

Category	Representative Algorithms	Primary Application	Advantages	Limitations
Traditional Machine Learning	SVM, KNN, Decision Tree, Random Forest, Logistic Regression, Naïve Bayes	Tumor classification	Simple, interpretable, suitable for small datasets	Manual feature extraction and limited scalability
Deep Learning	CNN, AlexNet, VGGNet, ResNet, DenseNet, GoogleNet	Automatic feature extraction and classification	High accuracy and robust feature learning	Requires large annotated datasets and GPUs
Segmentation Techniques	U-Net, 3D U-Net, V-Net, nnU-Net, FCN, FCM	Tumor localization and boundary detection	Precise segmentation and volume estimation	Sensitive to image quality and annotations
Classification Techniques	CNN, ResNet, DenseNet, SVM, Random Forest	Tumor type classification	High diagnostic performance	Class imbalance affects accuracy
Hybrid & Optimization Methods	CNN+SVM, GA, PSO, GWO, Jaya Optimization	Feature selection and parameter optimization	Improved accuracy and robustness	High computational complexity

Table 1: Categorization of AI Based Algorithms for Brain Tumor Detection

Table 1 categorizes the major artificial intelligence techniques used for brain tumor detection. Traditional machine learning methods are computationally efficient but depend on handcrafted feature extraction. Deep learning architectures automatically learn hierarchical features and achieve superior performance in both segmentation and classification. Segmentation techniques accurately delineate tumor boundaries, while classification methods identify tumor types with high diagnostic accuracy. Hybrid and optimization-based approaches further improve performance by combining feature learning with optimization strategies, although they increase computational complexity. This categorization provides a comprehensive comparison of existing methodologies and clearly illustrates the evolution of AI-based brain tumor detection techniques.

Literature Review Categorization

The literature on brain tumor detection can be broadly categorized into five major groups: traditional machine learning algorithms, deep learning architectures, segmentation techniques, classification methods, and hybrid optimization-based approaches. This categorization provides a systematic understanding of the evolution of artificial intelligence techniques and their applications in brain tumor detection.

Traditional machine learning algorithms, including Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Decision Tree, Random Forest, Logistic Regression, and Naïve Bayes, rely on handcrafted features extracted from MRI images. Although these methods are computationally efficient and suitable for small datasets, their performance depends heavily on feature engineering and is generally lower than that of deep learning models.

Deep learning architectures such as Convolutional Neural Networks (CNNs), AlexNet, VGGNet, ResNet, DenseNet, and U-Net have significantly improved brain tumor detection by automatically learning hierarchical image features. These models achieve superior accuracy in segmentation and classification tasks but require large annotated datasets and high computational resources.

Segmentation techniques focus on identifying tumor boundaries using methods such as thresholding, region growing, Fuzzy C-Means (FCM), K-means clustering, and U-Net-based architectures. Classification techniques categorize tumors into different classes, including glioma, meningioma, and pituitary tumors, using both conventional machine learning and deep learning approaches.

Hybrid and optimization-based methods integrate multiple algorithms, such as CNN with SVM, Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Grey Wolf Optimizer (GWO), to improve feature selection, parameter optimization, and overall detection accuracy. These approaches generally provide better performance than standalone models but involve higher computational complexity.

Overall, the literature demonstrates a clear transition from traditional machine learning techniques to advanced deep learning and hybrid models. While deep learning has achieved state-of-the-art performance, challenges such as limited annotated datasets, model interpretability, computational complexity, and clinical validation continue to motivate ongoing research in brain tumor detection.

IV. Datasets

Dataset	Images	MRI Modalities	Annotation
BraTS	2000+	T1 T2 FLAIR T1ce	Yes
TCGA	Large	MRI + Clinical	Yes
Figshare	3064	T1	Yes
REMBRANDT	MRI	Multi-modal	Yes

V. Conclusion

Brain tumor detection has significantly advanced through the adoption of machine learning and deep learning techniques, improving the accuracy of MRI-based tumor segmentation and classification. This survey categorized the existing literature into traditional machine learning, deep learning, segmentation, classification, and hybrid approaches, highlighting their applications, strengths, and limitations. While traditional machine learning methods are suitable for small datasets, deep learning models such as CNN, U-Net, ResNet, and DenseNet have demonstrated superior performance through automatic feature extraction and accurate tumor identification.

The review also emphasized the importance of benchmark datasets and evaluation metrics for assessing model performance. Despite these advancements, challenges such as limited annotated MRI datasets, class imbalance, domain shift, computational complexity, lack of explainability, and limited clinical validation continue to hinder real-world deployment. Hybrid models integrating deep learning with optimization techniques have shown promising results by improving detection accuracy and model robustness.

Future research should focus on explainable AI, federated learning, multi-modal MRI fusion, domain adaptation, and lightweight deep learning models to develop reliable and clinically applicable brain tumor detection systems. These advancements have the potential to enhance computer-aided diagnosis and support radiologists in the early detection and effective management of brain tumors.

VI. Challenges & Limitations

Despite remarkable progress in machine learning and deep learning for brain tumor detection, several challenges continue to limit their clinical adoption. One major issue is the limited availability of annotated MRI datasets, as expert labeling by radiologists is time-consuming and costly. Class imbalance within datasets often leads to biased model performance, particularly for rare tumor types. Additionally, variations in MRI scanners, imaging protocols, and patient demographics introduce cross-scanner variability and domain shift, reducing the generalizability of trained models across different healthcare institutions.

Deep learning models are also prone to overfitting due to the relatively small size of medical imaging datasets. Furthermore, the black-box nature of many advanced models raises concerns regarding interpretability and clinical trust. High computational requirements, privacy and security constraints associated with medical data sharing, and the lack of large-scale clinical validation further hinder real-world deployment. Addressing these challenges through explainable AI, federated learning, domain adaptation, and multi-center clinical studies will be essential for developing robust and reliable brain tumor detection systems.

VII. Future Scope

Future research in brain tumor detection should focus on developing robust, interpretable, and clinically applicable artificial intelligence models. Explainable Artificial Intelligence (XAI) techniques can improve the transparency of deep learning models and enhance clinicians' trust in automated diagnosis. Federated learning offers a promising solution for collaborative model training while preserving patient privacy across healthcare institutions. Multi-modal MRI data fusion and advanced architectures such as Vision Transformers can further improve tumor segmentation and classification accuracy. In addition, domain adaptation techniques are required to address variations in MRI scanners and imaging protocols, thereby improving model generalization across diverse clinical settings. Lightweight deep learning models and edge computing can facilitate real-time deployment in resource-constrained environments. Finally, large-scale multi-center clinical validation and seamless integration with hospital workflows are essential for translating AI-based brain tumour detection systems into routine clinical practice.

References

[1] S. K. Palvadi and K. S. Joseph, "Brain Tumor Detection Through Image Processing and Machine Learning Techniques," International Journal of Intelligent Systems and Applications in Engineering, vol. 12, no. 15s, pp. 382–389, Feb. 2024.
[2] S. K. Palvadi and K. S. Joseph, "An Overall Survey of Brain Tumor Detection with Improved Machine Learning and Deep Learning Techniques," International Journal of Intelligent Systems and Applications in Engineering, vol. 12, no. 15s, pp. 425–432, Feb. 2024.
[3] P. S. Kumar, "An Optimal Comparison of Brain Tumor Detection by Various Enhanced Machine Learning and Deep Learning Algorithms," Journal of Cardiovascular Disease Research, vol. 12, no. 7, 2021.
[4] P. S. Kumar, "Detection and Classification of Brain Tumors with Alzheimer Using Deep Learning and Convolutional Neural Networks," Journal of Cardiovascular Disease Research, vol. 10, no. 4, 2019.
[5] I. S. Rahat, T. Hossain, H. Ghosh, K. L. Kanth Reddy, S. K. Palvadi, and J. V. R. Ravindra, "Exploring Deep Learning Models for Accurate Alzheimer's Disease Classification Based on MRI Imaging," EAI Endorsed Transactions on Pervasive Health and Technology, vol. 10, 2024.
[6] G. Litjens et al., "A Survey on Deep Learning in Medical Image Analysis," Medical Image Analysis, vol. 42, pp. 60–88, 2017.
[7] D. Shen, G. Wu, and H.-I. Suk, "Deep Learning in Medical Image Analysis," Annual Review of Biomedical Engineering, vol. 19, pp. 221–248, 2017.
[8] M. Havaei et al., "Brain Tumor Segmentation with Deep Neural Networks," Medical Image Analysis, vol. 35, pp. 18–31, 2017.
[9] S. Pereira et al., "Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images," IEEE Transactions on Medical Imaging, vol. 35, no. 5, pp. 1240–1251, 2016.
[10] K. Kamnitsas et al., "Efficient Multi-Scale 3D CNN With Fully Connected CRF for Accurate Brain Lesion Segmentation," Medical Image Analysis, vol. 36, pp. 61–78, 2017.
[11] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," in Proc. MICCAI, 2015, pp. 234–241.
[12] Ö. Çiçek et al., "3D U-Net: Learning Dense Volumetric Segmentation From Sparse Annotation," in Proc. MICCAI, 2016.
[13] F. Milletari, N. Navab, and S. A. Ahmadi, "V-Net: Fully Convolutional Neural Networks for Volumetric Medical Image Segmentation," in Proc. 3DV, 2016.
[14] F. Isensee et al., "nnU-Net: A Self-Configuring Method for Deep Learning-Based Biomedical Image Segmentation," Nature Methods, vol. 18, no. 2, pp. 203–211, 2021.
[15] A. Hatamizadeh et al., "UNETR: Transformers for 3D Medical Image Segmentation," in Proc. IEEE/CVF Winter Conference on Applications of Computer Vision, 2022.
[16] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification With Deep Convolutional Neural Networks," Communications of the ACM, vol. 60, no. 6, pp. 84–90, 2017.
[17] K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," in Proc. ICLR, 2015.
[18] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in Proc. IEEE CVPR, 2016.
[19] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely Connected Convolutional Networks," in Proc. IEEE CVPR, 2017.
[20] C. Szegedy et al., "Going Deeper With Convolutions," in Proc. IEEE CVPR, 2015.
[21] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-Based Learning Applied to Document Recognition," Proceedings of the IEEE, vol. 86, no. 11, pp. 2278–2324, 1998.
[22] C. Cortes and V. Vapnik, "Support-Vector Networks," Machine Learning, vol. 20, no. 3, pp. 273–297, 1995.
[23] L. Breiman, "Random Forests," Machine Learning, vol. 45, pp. 5–32, 2001.
[24] T. Cover and P. Hart, "Nearest Neighbor Pattern Classification," IEEE Transactions on Information Theory, vol. 13, no. 1, pp. 21–27, 1967.
[25] J. R. Quinlan, C4.5: Programs for Machine Learning. San Francisco, CA, USA: Morgan Kaufmann, 1993.

[26] J. H. Holland, Adaptation in Natural and Artificial Systems. Ann Arbor, MI, USA: Univ. Michigan Press, 1975.
[27] J. Kennedy and R. Eberhart, "Particle Swarm Optimization," in Proc. IEEE ICNN, 1995, pp. 1942–1948.
[28] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey Wolf Optimizer," Advances in Engineering Software, vol. 69, pp. 46–61, 2014.
[29] S. Mirjalili, "Whale Optimization Algorithm," Advances in Engineering Software, vol. 95, pp. 51–67, 2016.
[30] R. V. Rao, "Jaya: A Simple and New Optimization Algorithm," International Journal of Industrial Engineering Computations, vol. 7, no. 1, pp. 19–34, 2016.
[31] B. H. Menze et al., "The Multimodal Brain Tumor Image Segmentation Benchmark (BraTS)," IEEE Transactions on Medical Imaging, vol. 34, no. 10, pp. 1993–2024, 2015.
[32] S. Bakas et al., "Advancing the Cancer Genome Atlas Glioma MRI Collections With Expert Segmentation Labels," Scientific Data, vol. 4, 2017.
[33] U. Baid et al., "The Brain Tumor Segmentation (BraTS) Challenge: Progress and Future Directions," Medical Image Analysis, 2024.
[34] R. R. Selvaraju et al., "Grad-CAM: Visual Explanations From Deep Networks via Gradient-Based Localization," International Journal of Computer Vision, vol. 128, pp. 336–359, 2020.
[35] S. M. Lundberg and S.-I. Lee, "A Unified Approach to Interpreting Model Predictions," in Proc. Advances in Neural Information Processing Systems (NeurIPS), 2017.