International Journal of Biomedicine 16(3) (2026) 306-313
http://dx.doi.org/10.21103/Article16(3)_RA2

REVIEW ARTICLE

INTERNATIONAL JOURNAL OF BIOMEDICINE

Deep Learning–Based Convolutional Neural Networks for Brain Tumor Detection on CT scans: A Systematic Review

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Abstract

This systematic review evaluates the efficacy and diagnostic performance of deep learning algorithms for detecting brain tumors from computed tomography (CT) data. To assess the diagnostic performance of convolutional neural network (CNN)-based models, a descriptive analysis of metrics such as accuracy, specificity, and precision was conducted. Results from nine recent studies demonstrated high diagnostic performance for deep learning methods. Most models achieved accuracy, precision, and specificity exceeding 95% in the differential diagnosis of neoplastic versus non-neoplastic lesions on imaging. These findings highlight the potential of CNNs to facilitate the early diagnosis of brain tumors, particularly in emergency settings where CT serves as the first-line imaging modality.
The analyzed studies employed a wide range of CNN architectures—from pre-trained models to custom-designed networks—yielding consistent and reliable results. However, several limitations were identified, including small sample sizes, reliance on retrospective data, insufficient external validation, and variations in approaches to interpreting results. Despite these limitations, the consistency of findings across independent studies confirms the reliability and practical potential of CNN-based methods for brain tumor detection in CT imaging. Future research should focus on prospective study designs, larger multicenter datasets, standardized reporting, and enhanced model interpretability to ensure safe and effective integration into clinical practice. (**International Journal of Biomedicine. 2026;16(3):306-313.**)

Keywords: deep learning • convolutional neural network • brain tumour • computed tomography

For citation: Ali S, Elbashir M, Hamzi A, Akour I, Sheikhain A, Al-Shahri R, Refaee T, Abdelrazig A, Omer AM. Deep Learning–Based Convolutional Neural Networks for Brain Tumor Detection on CT scans: A Systematic Review. International Journal of Biomedicine. 2026;16(3):306-313. doi:10.21103/Article16(3)_RA2

Abbreviations

AI, artificial intelligence; **CT**, computed tomography; **CNN**, convolutional neural network; **CAD**, computer-aided detection; **MRI**, magnetic resonance imaging; **ROC**, receiver operating characteristic

Introduction

Brain tumors represent a major global health challenge due to high morbidity and mortality rates.[1] A lack of timely diagnosis and treatment for these neoplasms can lead to severe neurological impairment and death. Consequently, diagnostic accuracy and timeliness play a pivotal role in determining patient prognosis and survival. Recent studies indicate that only about 35.6% of adult patients diagnosed with a malignant central nervous system tumor survive beyond the five-year mark.[2] Such statistics underscore the urgent need to develop methods for early and reliable diagnosis.

Clinical evidence consistently demonstrates that early detection and timely intervention significantly improve patient outcomes. For instance, in cases of glioblastoma multiforme—one of the most aggressive primary brain tumors—diagnosis within two weeks of symptom onset is associated with significantly higher survival rates compared to cases involving delayed diagnosis.[3] However, early diagnosis is challenging because brain tumors often present with nonspecific neurological symptoms common to a wide range of other conditions.

The diagnostic process is further complicated by the need to differentiate suspected brain tumors from numerous other conditions. Imaging findings and clinical presentations can mimic metastatic lesions, inflammatory processes, vascular anomalies, or other non-neoplastic neurological disorders.[4] Conversely, some brain neoplasms may lack the classic signs of a space-occupying lesion, making it difficult to distinguish them from benign processes during both imaging and histopathological examination.[5] These challenges highlight the need for reliable diagnostic tools to support clinical decision-making.

Medical imaging techniques play a pivotal role in the diagnosis and management of patients with brain tumors. Advances in computed tomography (CT) and magnetic resonance imaging (MRI), alongside the development of specialized imaging modalities, have significantly enhanced the ability to detect and characterize pathological lesions.[6] CT remains a first-line imaging modality in many clinical scenarios—particularly in emergency medicine—due to its rapid image acquisition, widespread availability, and cost-effectiveness. Despite these advantages, CT has several known limitations. Compared to MRI, CT offers lower soft-tissue contrast, and artifacts caused by the "beam hardening" effect as radiation passes through the skull can obscure subtle pathological changes. Furthermore, the use of ionizing radiation and limited spatial resolution reduces the method's diagnostic sensitivity, especially when detecting small or isodense lesions. Such limitations can lead to missed pathologies and significant inter-observer variability among radiologists, particularly under high workloads. To address these issues, the potential of computer-aided detection (CAD) systems as an assistive tool for reviewing imaging results is being investigated. Early CAD methods relied heavily on manually extracted image features, such as intensity distribution, texture descriptors, and morphological characteristics. However, these methods often lacked robustness and generalizability, limiting their diagnostic efficacy and potential for clinical implementation.[7]

In recent years, artificial intelligence, particularly deep learning, has emerged as a powerful tool, fundamentally transforming approaches to medical image analysis. Deep convolutional neural networks (CNNs) can automatically learn to extract complex hierarchical features directly from raw imaging data, eliminating the need for manual feature engineering. Consequently, CNN-based models have demonstrated state-of-the-art performance across a wide range of radiological tasks, including the detection, classification, and segmentation of pathological lesions. In the field of neuroimaging, several studies have demonstrated the high diagnostic accuracy of CNN models for analyzing CT data; some achieved accuracy rates of approximately 96%, with similarly high sensitivity and specificity.[6] These findings suggest that deep learning methods can complement radiologists' expertise, reduce diagnostic variability, and enhance clinical efficiency.[8] Furthermore, recent efforts have focused on developing lightweight, computationally efficient CNN architectures that enable real-time analysis and deployment in clinical settings with limited computing resources, further underscoring the potential of AI for CT image interpretation.

Despite these promising results, the existing body of evidence on deep learning for brain tumor detection in CT images remains fragmented. Existing reviews in neuro-oncology primarily focus on MRI analysis methods, whereas systematic summaries of data specifically concerning computed tomography are relatively scarce.[9] Moreover, individual studies vary significantly in terms of the CNN architectures employed, training strategies, dataset composition, and evaluation metrics. Such methodological heterogeneity complicates direct comparisons of results and limits the ability to draw clinically relevant, actionable conclusions about the efficacy and reliability of deep learning models for CT data analysis.[10]

Concurrently, promising approaches such as secure federated deep learning, implemented on high-performance computing (HPC) infrastructure, are attracting increasing attention. These are considered scalable solutions that ensure privacy during collaborative analysis of medical images. Federated learning enables multiple medical institutions to jointly train deep learning models without exchanging raw patient data, thereby addressing critical issues related to data protection and regulatory compliance. When combined with secure aggregation methods and HPC resources, federated approaches have demonstrated high efficacy and strong generalization capabilities in classifying brain tumors using MRI data from heterogeneous sources.[11] These advances underscore the growing importance of computational efficiency, data diversity, and privacy preservation in modern medical imaging research. Although most federated learning applications have been investigated in the context of brain tumor analysis using MRI data, these approaches are becoming increasingly relevant for CT as well—particularly in emergency care settings and multicenter studies, where data-sharing restrictions, variations in scanner characteristics, and the need for rapid system deployment pose significant challenges.

The accurate classification of brain tumors is a critical task in medical imaging, directly influencing diagnosis, treatment planning, and patient survival. Early detection not only improves clinical outcomes but also facilitates the development of more effective and targeted therapeutic strategies.[12] More broadly, machine learning methods—a key field of artificial intelligence that employs probabilistic approaches and optimization algorithms to extract meaningful patterns from vast, complex datasets—drive progress across various stages of patient management in neuro-oncology, including diagnosis, prognosis, and the monitoring of treatment efficacy.[13,14]

In this context, a comprehensive and targeted analysis of existing scientific data is essential. This systematic review aimed to evaluate the performance of deep learning algorithms in detecting brain tumors using computed tomography (CT) data. By systematically synthesizing performance metrics such as accuracy, specificity, and precision, the study assessed the diagnostic value, reliability, and limitations of CNN- based models. Furthermore, the review sought to identify common methodological approaches, persistent challenges, and research gaps that may affect model reproducibility and generalizability, and to assess their potential for implementation in clinical practice across various medical institutions.

Methodology

Information Sources and Search Strategy

A comprehensive systematic search was conducted across electronic databases, including PubMed, Scopus, and Google Scholar, to identify relevant studies. The search employed combinations of keywords and MeSH terms, such as "deep learning," "convolutional neural network," "brain tumor," and "CT imaging," along with Boolean operators to ensure a comprehensive selection. The search was limited to English-language, peer-reviewed articles published between 2017 and 2024.

All retrieved records were uploaded to the Rayyan QCRI platform, a web-based tool designed to facilitate the study selection phase of a systematic review. Duplicates were removed automatically, then manually verified. This review was conducted and reported in accordance with the PRISMA-DTA guidelines for diagnostic test accuracy studies.

Study Selection Process

Two researchers independently assessed the titles and abstracts against the established inclusion criteria. Full-text articles were obtained for all potentially eligible studies and were also independently evaluated by the same researchers. Disagreements were resolved through discussion; if consensus was not reached, a third researcher was brought in. The study selection process and reasons for exclusion at each stage are presented in the PRISMA flow diagram (Figure 1).

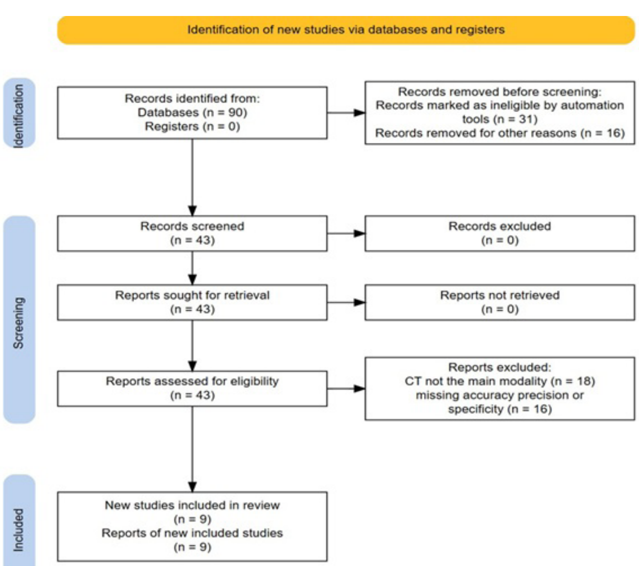

Figure 1. *Study selection.*

The review included peer-reviewed original research articles involving human subjects that employed deep learning CNNs to detect or classify brain tumors using CT imaging data and reported quantitative metrics of diagnostic performance (accuracy, sensitivity, specificity, or precision). Only full-text journal articles in English were considered.

Studies based exclusively on MRI or other imaging modalities (other than CT) were excluded, as were review articles, editorials, conference abstracts, case reports, animal studies, and studies using phantoms. Additionally, studies lacking sufficient methodological detail or key quantitative performance metrics (e.g., unclear descriptions of the CNN methodology or insufficient data on diagnostic accuracy) were excluded. All inclusion and exclusion criteria were defined a priori and applied consistently throughout the selection process.

Rationale for Quantitative Synthesis Approach

Due to the significant heterogeneity in CNN architectures, dataset characteristics, validation strategies, and reporting methods for results—as well as the incomplete reporting of variability measures and confidence intervals in primary studies—conducting a formal meta-analysis to estimate pooled effect sizes was not feasible. Consequently, the synthesis of results was conducted using a structured, descriptive, and comparative quantitative approach, in accordance with the PRISMA-DTA guidelines for diagnostic test accuracy reviews, which do not allow statistical pooling of data.

This systematic review was not registered with PROSPERO.

The PRISMA flow diagram illustrates the study screening and inclusion process: identification of records, removal of duplicates, screening of records by title and abstract, assessment of full-text versions against eligibility criteria, and the final list of included studies.

All titles and abstracts of identified records were screened for inclusion in the review. Two researchers independently evaluated each record based on predefined selection criteria. Following the removal of duplicates, titles and abstracts of all remaining records were screened, and full-text articles were retrieved for potentially eligible studies. Subsequently, the full texts were evaluated in detail against inclusion and exclusion criteria. The number of studies included and excluded at each stage is shown in Figure 1, prepared in accordance with standard PRISMA methodology.

This systematic review was conducted and reported in accordance with the PRISMA-DTA guidelines for diagnostic test accuracy studies.

Data Extraction

Data extraction was performed independently by two researchers using a standardized and pilot-tested data extraction form. Extracted information included study identifiers (authors, publication year, country), study design characteristics (sample size and study population), details on CNN models (architecture and training data), and performance metrics such as accuracy, specificity, precision, and the area under the ROC curve (AUC). Where available, data on validation strategies (e.g., internal or external) and dataset characteristics were also collected, as these are essential for interpreting model performance and subsequently assessing the risk of bias.

All extracted data were organized in Microsoft Excel tables to facilitate comparison and synthesis. Disagreements between researchers were resolved through discussion and consensus. To ensure transparency and reproducibility, the complete data extraction table and supplementary materials are available from the corresponding author upon reasonable request.

Risk of Bias Assessment

Figure 2 presents a summary of the risk-of-bias assessment for all studies included in the review. The bar chart illustrates the proportion of studies with low, high, or unclear risk of bias across each methodological domain. Overall, most studies showed a low risk of bias, particularly in the domains of outcome measurement and model performance assessment, indicating consistently high methodological quality. However, some studies exhibited an unclear or elevated risk of bias in domains related to patient selection and the handling of confounding factors, reflecting variations in study design and data reporting practices. The assessment was conducted in accordance with established guidelines for systematic reviews of diagnostic accuracy studies.

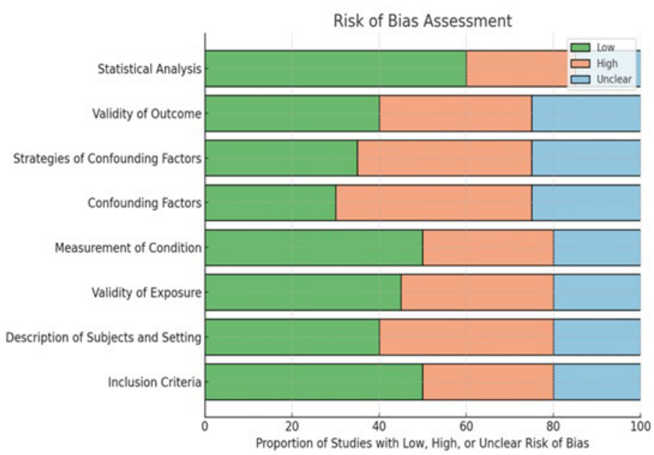

Figure 2. *Risk of bias assessment.*

The risk of bias for each included study was assessed across specific domains using the QUADAS-2 tool, which is widely recommended for systematic reviews of diagnostic accuracy studies. Four key domains were evaluated: patient selection, the index test (CNN-based CT model), the reference standard, and flow and timing. The risk of bias in each domain was classified as low, high, or unclear based on predefined criteria, including the clarity of the inclusion criteria, the adequacy of the dataset and population descriptions, the validity of outcome labeling, the correctness of the analytical methods, and the consideration of potential confounding factors.

Figure 2 presents the distribution of studies across risk categories for each domain. The color-coded visualization reflects the overall consistency of methodological quality across the included CNN-based CT studies. As shown in Figure 2, a low risk of bias predominated across most domains, particularly regarding outcome assessment and model quality evaluation, thereby increasing confidence in the reported diagnostic performance. Moderate concerns arose primarily from potential confounding factors, including variations in dataset size, class imbalance, and differences in validation strategies. These methodological aspects were taken into account when interpreting the findings, enabling a balanced and cautious assessment of the evidence base while avoiding overestimating numerical performance metrics.

To assess the robustness of the findings, a sensitivity analysis was conducted to evaluate the impact of excluding studies with a high risk of bias based on one or more critical criteria. Excluding such studies did not substantially alter the overall pattern of diagnostic performance observed in the remaining studies, indicating that the main conclusions were not driven by studies with higher methodological risk.

Risk of bias assessments were conducted using the QUADAS-2 framework, with results summarized and visualized using standard spreadsheet software. Findings from the risk of bias evaluation were considered in the descriptive synthesis of results, particularly when comparing studies with differing methodological characteristics. Domains demonstrating higher or unclear risk of bias, especially those related to data selection and confounding control, were recognized as potential sources of variability across studies. ChatGPT by OpenAI was used to enhance figure presentation. The authors independently verified all scientific information and approved the final version of the manuscript.

The methodological quality of each included study was independently assessed by two experts using established risk of bias criteria adapted for diagnostic accuracy research. Aspects such as patient selection, image acquisition and interpretation, outcome measurement, and data transparency were evaluated. The risk of bias in each category was classified as low, high, or unclear in accordance with published guidelines; disagreements were resolved through discussion. An overall assessment of study quality was conducted using a cautious approach, placing greater weight on aspects most critical to diagnostic validity.

Results

Table 1 presents pre-trained CNN architectures, including ResNet-50, EfficientNet-B0, MobileNet-V1, VGG-16, and GoogLeNet. Accuracy metrics ranged from approximately 94% to 99%, with the highest values observed in studies utilizing EfficientNet-B0, ensemble models (combinations of multiple architectures), and 3D CNNs with data fusion. Custom-designed CNN architectures also demonstrated high diagnostic accuracy, particularly when employing optimization strategies or modules based on expert knowledge. Sensitivity values were inconsistently reported across the included studies, and information on sample size and validation type was frequently unavailable or limited to internal validation only. Overall, the results indicate high diagnostic performance across various CNN-based approaches, alongside diverse model designs and data representation methods (Figures 3-5).

Table 1.
Characteristics of selected studies.

Study (First Author, Year)	CNN Architecture	Specificity, %	Accuracy, %	Precision, %
Woźniak et al., 2023 [17]	Custom 8-layer CNN + CLM support	96.00	95.00	95.00
Anjum et al., 2022 [20]	ResNet-50 (transfer learning)	96.00	94.00	96.00
ARI et al., 2018 [31]	EfficientNet-B0 (transfer learning)	97.12	97.18	96.80
Moe et al., 2019 [30]	MobileNet-V1 (transfer learning)	97.00	97.00	97.00
Mahmud et al., 2023 [19]	Custom CNN (hyperparameter tuned)	97.00	93.30	90.00
Negm et al., 2023 [18]	VGG-16 + ResNet (ensemble)	98.74	98.45	97.93
Mehrotra et al., 2020 [25]	GoogLeNet (transfer learning)	99.29	99.04	99.30
Rao et al., 2019 [24]	Custom CNN + knowledge module	94 .00	93	88.00
Almadhoun et al., 2022 [32]	3D CNN + data fusion	99.00	99.88	99.00

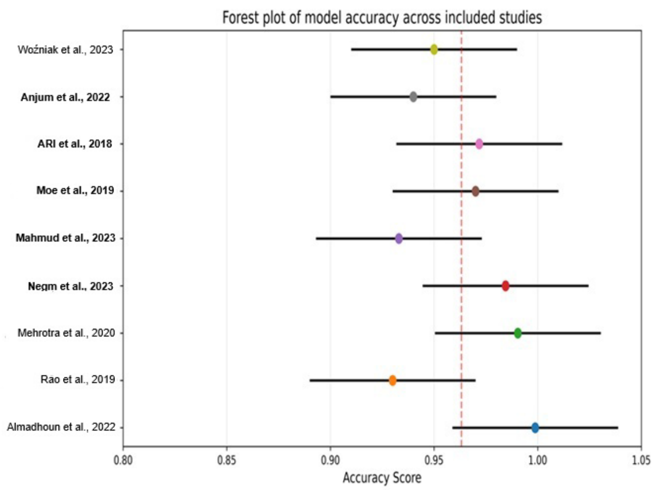

Figure 3. *Forest plot showing individual study accuracy estimates for CNN-based brain tumor detection using CT imaging. Each square represents the accuracy reported by an individual study, with horizontal lines indicating the corresponding confidence intervals where available. Variability in accuracy reflects differences in CNN architectures, dataset characteristics, and validation strategies.*

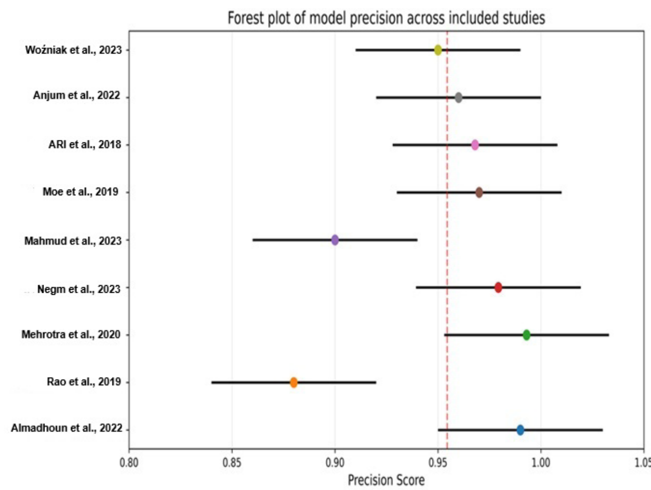

Figure 4. *Forest plot illustrating model precision (positive predictive value, %) across the included studies. Precision values varied between studies, reflecting differences in CNN architectures, training strategies, and dataset characteristics, including the use of transfer learning, ensemble models, and custom-designed networks. The figure is presented to facilitate visual comparison of precision performance across individual studies.*

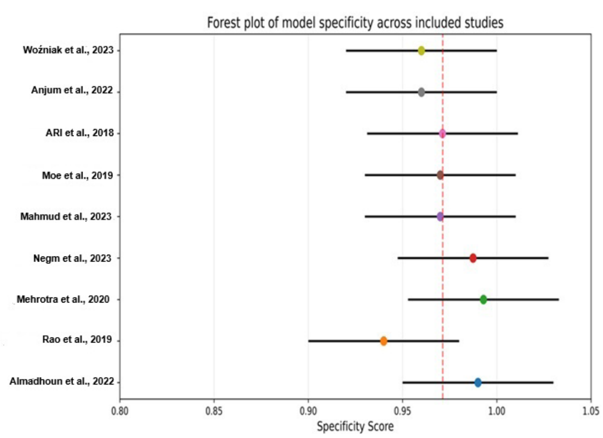

Figure 5. *Forest plot illustrating specificity values (%) reported across the included studies. Specificity varied between studies, reflecting differences in CNN architectures, training strategies, and dataset characteristics, including the use of transfer learning, ensemble approaches, and custom-designed networks. The figure is presented to support visual comparison of specificity performance across individual studies.*

Discussion

This systematic review demonstrates that deep learning methods, specifically CNN-based models, consistently achieve high diagnostic performance for detecting brain tumors on CT scans. Across the nine studies included in the review, the CNN architecture demonstrated high accuracy, specificity, and precision, underscoring its robust ability to distinguish between cases with and without tumors. These findings reinforce the growing role of artificial intelligence in extracting clinically significant information from standard CT scans, which remain widely available and are frequently utilized in emergencies and acute care settings.[15]

Clinical Significance of AI in CT Image Analysis

A key strength of this review is its exclusive focus on CT-based tumor detection. This addresses a gap in the scientific literature on AI applications in neuroimaging, where the primary focus has historically been on MRI-based methods. Although MRI-related studies predominated during the initial selection phase, limiting the sample to CT-based research enabled an assessment specific to this imaging modality, thereby eliminating confounding factors. Given that CT is often the first-line imaging modality in emergency departments—owing to its rapid image acquisition, accessibility, and suitability for patients in critical or unstable condition—AI-assisted CT interpretation could facilitate earlier tumor detection when MRI is unavailable, delayed, or contraindicated.[16] AI-based CT analysis should not be viewed as a replacement for MRI; rather, it serves as a complementary tool that streamlines patient triage and supports timely clinical decision-making in time-critical situations.

Consistency of Performance Metrics across Various CNN Architectures

Despite differences in model architectures and training strategies, all the studies included in the review yielded favorable diagnostic results, underscoring the reliability of CNN-based methods for detecting brain tumors in CT scans. Models employing transfer learning based on established architectures—such as ResNet-50, EfficientNet-B0, MobileNet-V1, and GoogLeNet—consistently demonstrated high performance. This confirms the effectiveness of pre-trained neural networks in medical imaging, particularly when training datasets are limited.[17,18]

More advanced approaches, including ensemble models that combine different architectures (e.g., VGG-16 and ResNet), achieved further improvements in specificity and accuracy. This supports the hypothesis that integrating diverse feature representation methods enhances the system's ability to distinguish between pathological and normal states.[19] Furthermore, studies using 3D CNNs combined with data fusion techniques reported the highest accuracy, highlighting the importance of volumetric information and spatial context for brain tumor detection in CT data. Custom-designed CNN architecture also yielded competitive results when optimized through hyperparameter tuning or curriculum learning, although the slightly lower accuracy observed in some studies may reflect dataset imbalance, limited sample size, or increased model complexity.[20,21]

Generalizability, Scanner Variability, and Reliability

Consistently high specificity and accuracy across studies indicate that CNN-based systems can reduce false-positive rates. This is crucial for clinical implementation, as it helps avoid unnecessary follow-up examinations and patient anxiety. However, model performance was influenced by CT image acquisition protocols and specific scanner characteristics. Optimal results were often observed when training and testing data originated from similar distributions or were acquired using similar equipment.[21,22] This dependency highlights the issue of "domain shift" in applying AI to radiology and underscores the need for multi-center datasets—acquired with equipment from various manufacturers—to ensure robust generalizability of results across diverse clinical settings.

Risk of Bias, Validation Practices, and Interpretation of Performance Metrics

The studies were predominantly retrospective in nature and varied in sample size and patient selection criteria. Typical limitations included the narrow scope of the groups studied and insufficient descriptions of confounding factors,[23,24] which could lead to inflated efficacy estimates when test datasets were highly similar to training datasets. Furthermore, not all studies reported sensitivity data (with greater emphasis often placed on accuracy, specificity, and precision), limiting the ability to comprehensively evaluate model performance, particularly with respect to false-negative results. Consistent with broader trends in the AI radiology literature, studies incorporating external validation generally showed a slight decline in performance metrics relative to internal validation results, reflecting the impact of data heterogeneity and domain shift.[18,25] Only a small fraction of the studies evaluated models on independent external datasets; these datasets often lacked geographic and demographic diversity and provided insufficient descriptions of population characteristics. Furthermore, none of the included studies conducted formal temporal validation across different time periods, limiting the ability to assess model stability over time. Although a heightened risk of bias in certain methodological aspects reduced confidence in the accuracy of quantitative metrics, no study was deemed methodologically flawed to the extent that its conclusions were called into question. Overall, the available evidence supports the efficacy of CNN-based approaches for detecting brain tumors in CT scans; however, it highlights the need for cautious interpretation of near-perfect performance metrics and for adopting more rigorous validation strategies in future research.[26,23]

Practical Significance and Future Directions

No clear evidence of publication bias was found, although the limited number of studies reporting low performance or negative results may reflect either publication bias or the inherently high efficacy of CNN-based methods in this field.[27,28] Despite the relatively small number of eligible studies, due to the specific focus on CT imaging, the consistency of findings across independent studies reinforces confidence in the conclusions.[29,30] Emerging research indicates that advanced post-processing techniques and optimized image representations can further suppress false positives and enhance object detection performance.[19] Future research should prioritize prospective designs, standardized reporting systems, and rigorous external and temporal validation across diverse clinical settings. Addressing these issues is crucial for confirming the reliability of CT-based tumor detection systems that utilize CNNs and for ensuring their responsible implementation in clinical practice.

Conclusion

This systematic review indicates that deep learning models, specifically CNN-based architectures, demonstrate consistently high diagnostic performance in detecting brain tumors on CT images. In the studies analyzed, CNN-based methods exhibited high accuracy, specificity, and precision, comparable to expert assessment results reported in previous literature. This highlights their potential as an assistive tool in diagnostic radiology, particularly in emergency care and resource-constrained settings.

By focusing specifically on CT images, this review addresses a significant gap in the existing literature and demonstrates that CNNs can effectively extract informative features despite inherent CT limitations, including reduced soft-tissue contrast and inter-observer variability in interpretation. However, many studies relied on retrospective datasets with limited diversity and lacked robust external or temporal validation, raising questions about the generalizability of the findings.

Overall, deep learning with CNNs is a promising and evolving approach for improving brain tumor detection in CT data. Despite encouraging results, widespread clinical implementation requires larger multicenter studies, prospective validation, and performance assessment in real-world clinical settings. This review can serve as a foundation for future research aimed at the safe, effective, and evidence-based integration of artificial intelligence tools into neuro-oncology practice involving CT imaging.

Data Availability Statement

All data associated with this study will be available based on the reasonable request to corresponding author.

AI Statement

The authors acknowledge ChatGPT-4 for assistance with proofreading and language editing during the writing process. After using this tool, the authors reviewed and edited the content. The authors take full responsibility for the final version of the manuscript.

Author Contributions

Sara Ali: Conceptualization, validation, formal analysis, investigation, data curation, writing—original draft, writing—review and editing, visualization, supervision, project administration.
Meaad Elbashir: Investigation, data curation, writing—original draft, and writing—review and editing.
Almohannad Hamzi: Investigation, data curation
Imad Akour: Investigation, data curation
Anwar Sheikhain: Investigation, data curation
Raed Al-Shahri: Investigation, data curation
Turkey Refaee: Validation, writing—review and editing, supervision.
Ali Abdelrazig: Investigation, data curation, visualization, and writing—original draft
Awatif M. Omer: Investigation, and writing—original draft.

All authors have approved the final article.

Acknowledgment

The authors would like to express their appreciation to all individuals who contributed to the preparation of this manuscript. Their support and valuable insights helped improve the quality of this work.

Conflict of Interest

The authors have declared no conflict of interest.

Funding Resource

Not applicable.

References

1. Kumar A, Pandey SK, Varshney N, Singh KU, Singh T, Shah MA. Distinctive approach in brain tumor detection and feature extraction using biologically inspired DWT method and SVM. Sci Rep. 2023 Dec 20;13(1):22735. doi: 10.1038/s41598-023-50073-9. PMID: 38123666; PMCID: PMC10733354.
2. Dorfner FJ, Patel JB, Kalpathy-Cramer J, Gerstner ER, Bridge CP. A review of deep learning for brain tumor analysis in MRI. NPJ Precis Oncol. 2025 Jan 3;9(1):2. doi: 10.1038/s41698-024-00789-2. PMID: 39753730; PMCID: PMC11698745.
3. Kawauchi D, Ohno M, Miyakita Y, Takahashi M, Yanagisawa S, Omura T, Yoshida A, Kubo Y, Igaki H, Ichimura K, Narita Y. Early Diagnosis and Surgical Intervention Within 3 Weeks From Symptom Onset Are Associated With Prolonged Survival of Patients With Glioblastoma. Neurosurgery. 2022 Nov 1;91(5):741-748. doi: 10.1227/neu.0000000000002096. Epub 2022 Aug 15. Erratum in: Neurosurgery. 2023 Feb 01;92(2):e44. doi: 10.1227/neu.0000000000002281. PMID: 35951724; PMCID: PMC9531976.
4. Mesfin FB, Karsonovich T, Al-Dhahir MA. Gliomas. 2024 Aug 12. In: StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing; 2026 Jan–. PMID: 28722904.
5. Behin A, Hoang-Xuan K, Carpentier AF, Delattre JY. Primary brain tumours in adults. Lancet. 2003 Jan 25;361(9354):323-31. doi: 10.1016/S0140-6736(03)12328-8. PMID: 12559880.
6. Bruzzone MG, D'Incerti L, Farina LL, Cuccarini V, Finocchiaro G. CT and MRI of brain tumors. Q J Nucl Med Mol Imaging. 2012 Apr;56(2):112-37. PMID: 22617235.
7. Aberle D, El-Saden S, Abbona P, Gomez A, Motamedi K, Ragavendra N et al. A primer on imaging anatomy and

physiology. In Medical imaging informatics. Boston, MA: Springer US, 2009:15-90.
8. Mienye ID, Swart TG, Obaido G, Jordan M, Ilono P. Deep Convolutional Neural Networks in Medical Image Analysis: A Review. Information. 2025; 16(3):195. doi: 10.3390/info16030195
9. Khalighi S, Reddy K, Midya A, Pandav KB, Madabhushi A, Abedalthagafi M. Artificial intelligence in neuro-oncology: advances and challenges in brain tumor diagnosis, prognosis, and precision treatment. NPJ Precis Oncol. 2024 Mar 29;8(1):80. doi: 10.1038/s41698-024-00575-0. PMID: 38553633; PMCID: PMC10980741.
10. Zhou SK, Greenspan H, Davatzikos C, Duncan JS, van Ginneken B, Madabhushi A, Prince JL, Rueckert D, Summers RM. A review of deep learning in medical imaging: Imaging traits, technology trends, case studies with progress highlights, and future promises. Proc IEEE Inst Electr Electron Eng. 2021 May;109(5):820-838. doi: 10.1109/JPROC.2021.3054390.
11. Appasami G, Savarimuthu N. Cross-dataset performance evaluation and secure federated learning with weighted model aggregation for MRI brain tumor image classification. J Supercomput. 2025;81:1555.
12. Appasami G, Savarimuthu N. Federated learning for secure medical MRI brain tumor image classification. Eur Phys J Spec Top. 2025;*234:*4813–4827. doi:10.1140/epjs/s11734-025-01516-z
13. Appasami G, Savarimuthu N. A novel lightweight CNN design for MRI brain tumor image classification with performance-driven optimization. Discov Computing. 2025;28:206. doi:10.1007/s10791-025-09603-4
14. Al-Rahbi A, Al-Habsi T, Al-Suli A, et al. Artificial intelligence use in diagnosis, grading, and segmentation of neuro-oncology: a narrative review. Egypt J Neurol Psychiatry Neurosurg.2025;61:54. doi:10.1186/s41983-025-00980-7
15. Patil V, Madgi M, Kiran A. Early prediction of Alzheimer's disease using convolutional neural network: a review. Egypt J Neurol Psychiatry Neurosurg. 2022;58:130. doi.org/10.1186/s41983-022-00571-w
16. Illimoottil M, Ginat D. Recent Advances in Deep Learning and Medical Imaging for Head and Neck Cancer Treatment: MRI, CT, and PET Scans. Cancers (Basel). 2023 Jun 21;15(13):3267. doi: 10.3390/cancers15133267. PMID: 37444376; PMCID: PMC10339989.
17. Woźniak M, Siłka J, Wieczorek M. Deep neural network correlation learning mechanism for CT brain tumor detection. Neural Comput & Applic.2023;**35:**14611–14626 (2023). doiDoi:10.1007/s00521-021-05841
18. Negm N, Aldehim G, Nafie FM, Marzouk R, Assiri M, Alsaid MI, et al. Intracranial haemorrhage diagnosis using willow catkin optimization with voting ensemble deep learning on CT brain imaging. IEEE Access. 2023;11:75474-75483. doi:10.1109/ACCESS.2023.3297281
19. Mahmud MI, Mamun M, Abdelgawad A. A Deep Analysis of Brain Tumor Detection from MR Images Using Deep Learning Networks. Algorithms. 2023; 16(4):176. doi:10.3390/a16040176
20. Anjum S, Hussain L, Ali M, Alkinani MH, Aziz W, Gheller S, et al. Detecting brain tumors using deep learning convolutional neural network with transfer learning approach. International Journal of Imaging Systems and Technology. 2022;32(1), 307-323. doi:10.1002/ima.22641 12
21. Chang K, Balachandar N, Lam C, Yi D, Brown J, Beers A, Rosen B, Rubin DL, Kalpathy-Cramer J. Distributed deep learning networks among institutions for medical imaging. J Am Med Inform Assoc. 2018 Aug 1;25(8):945-954. doi: 10.1093/jamia/ocy017. PMID: 29617797; PMCID: PMC6077811.
22. Hossain T, Shishir FS, Ashraf M, Nasim MA, Muhammad Shah F. Brain Tumor Detection Using Convolutional Neural Network. 2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT*)*, 2019:1-6.
23. Ramspek CL, Jager KJ, Dekker FW, Zoccali C, van Diepen M. External validation of prognostic models: what, why, how, when and where? Clin Kidney J. 2020 Nov 24;14(1):49-58. doi: 10.1093/ckj/sfaa188. PMID: 33564405; PMCID: PMC7857818.
24. Rao SKV, Lingappa B. Image Analysis for MRI Based Brain Tumour Detection Using Hybrid Segmentation and Deep Learning Classification Technique. International Journal of Intelligent Engineering & Systems. 2019;12(5). doi: 10.22266/ijies2019.1031.06
25. Mehrotra R, Ansari MA, Agrawal R, Anand RS. A transfer learning approach for AI-based classification of brain tumors. Machine Learning with Applications.2020;2:100003. doi:10.1016/j.mlwa.2020.100003
26. Anderson AW, Marinovich ML, Houssami N, Lowry KP, Elmore JG, Buist DSM, Hofvind S, Lee CI. Independent External Validation of Artificial Intelligence Algorithms for Automated Interpretation of Screening Mammography: A Systematic Review. J Am Coll Radiol. 2022 Feb;19(2 Pt A):259-273. doi: 10.1016/j.jacr.2021.11.008.
27. Kaifi R. A Review of Recent Advances in Brain Tumor Diagnosis Based on AI-Based Classification. Diagnostics (Basel). 2023 Sep 20;13(18):3007. doi: 10.3390/diagnostics13183007. PMID: 37761373; PMCID: PMC10527911.
28. Mäenpää SM, Korja M. Diagnostic test accuracy of externally validated convolutional neural network (CNN) artificial intelligence (AI) models for emergency head CT scans - A systematic review. Int J Med Inform. 2024 Sep;189:105523.
29. Takao H, Amemiya S, Kato S, Yamashita H, Sakamoto N, Abe O. Deep-learning single-shot detector for automatic detection of brain metastases with the combined use of contrast-enhanced and non-enhanced computed tomography images. Eur J Radiol. 2021 Nov;144:110015. doi: 10.1016/j.ejrad.2021.110015. Epub 2021 Nov 1. PMID: 34742108.
30. Moe YM, Groendahl AR, Mulstad M, Tomic O, Indahl U, Dale E, et al. Deep learning for automatic tumour segmentation in PET/CT images of patients with head and neck cancers. arXiv preprint arXiv:1908.00841. doi:10.48550/arXiv.1908.00841
31. ARI A, HANBAY D. Deep learning based brain tumor classification and detection system. Turk J Elec Eng & Comp Sci (2018) 26: 2275 – 2286. doi:10.3906/elk-1801-8
32. Almadhoun HR, Abu-Naser SS. Detection of Brain Tumor Using Deep Learning. Int J Acad Eng Res (IJAER). 2022;6(3):29–47.

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