DEEP LEARNING APPLICATIONS IN BRAIN TUMOR CLASSIFICATION ON MAGNETIC RESONANCE IMAGING: A DIAGNOSTIC ACCURACY STUDY

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ABSTRACT

Background:

Brain tumours are among the most challenging neurological disorders due to their diverse histopathological characteristics and overlapping imaging features. Magnetic Resonance Imaging (MRI) is the preferred imaging modality for the evaluation of brain tumours because of its superior soft-tissue contrast and multiplanar imaging capability. However, accurate tumor classification remains dependent on radiologist expertise and may be subject to interobserver variability. Recent advances in artificial intelligence, particularly deep learning, have shown promising results in automated image analysis and tumor classification, with the potential to improve diagnostic accuracy and support clinical decision-making.

Aim:

To evaluate the diagnostic accuracy of deep learning applications in the classification of brain tumours on Magnetic Resonance Imaging.

Objectives:

1. To determine the diagnostic accuracy of a deep learning model for classifying brain tumours on MRI using histopathological diagnosis as the reference standard.
2. To compare the diagnostic performance of the deep learning model with radiologist interpretation in the classification of brain tumours on MRI.

Materials and Methods:

A hospital-based diagnostic accuracy study was conducted in the Department of Radiodiagnosis in collaboration with the Departments of Neurosurgery and Pathology. A total of 30 patients with histopathologically confirmed brain tumours who fulfilled the inclusion and exclusion criteria were included. Preoperative MRI examinations were analysed using a validated deep learning algorithm. The deep learning predictions were compared with histopathological diagnosis, which served as the gold standard, and with conventional radiologist interpretation. Diagnostic performance was assessed using sensitivity, specificity, positive predictive value, negative predictive value, overall accuracy, receiver operating characteristic (ROC) curve analysis, area under the curve (AUC), Cohen's kappa coefficient, and McNemar's test. A p-value <0.05 was considered statistically significant.

Results:

The mean age of the study participants was 44.8 ± 13.2 years, with a male predominance (56.7%). Glioma was the most common tumor (40.0%), followed by meningioma (26.7%), pituitary adenoma (16.7%), brain metastasis (10.0%), and other tumors (6.6%). The deep learning model correctly classified 27 of the 30 cases. The model demonstrated a sensitivity of 93.3%, specificity of 86.7%, positive predictive value of 87.5%, negative predictive value of 92.9%, and an overall diagnostic accuracy of 90.0%. The area under the ROC curve was 0.94, indicating excellent diagnostic performance. Comparison with histopathology showed no statistically significant difference (McNemar test, $p = 0.564$). The deep learning model also demonstrated slightly higher sensitivity, specificity, overall accuracy, and agreement with histopathology than conventional radiologist interpretation, although the difference was not statistically significant ($p = 0.317$).

Conclusion:

Deep learning demonstrated excellent diagnostic performance in the classification of brain tumours on MRI and showed strong agreement with histopathological diagnosis. It performed comparably to conventional radiologist interpretation and may serve as a valuable clinical decision-support tool for improving diagnostic accuracy, reducing observer variability, and facilitating timely treatment planning. Larger multicentre studies with standardized imaging protocols are recommended to further validate these findings before routine clinical implementation.

Keywords: Brain Tumor, Deep Learning, Artificial Intelligence, Magnetic Resonance Imaging, MRI, Diagnostic Accuracy, Convolutional Neural Network, Histopathology.

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INTRODUCTION

Brain tumours comprise a heterogeneous group of benign and malignant neoplasms arising from the brain parenchyma, meninges, cranial nerves, pituitary gland, or metastatic deposits from systemic malignancies. Although brain tumours account for a relatively small proportion of all cancers, they are associated with substantial morbidity, neurological disability, and mortality owing to their critical intracranial location. The clinical manifestations vary depending on tumor type, size, and anatomical location and commonly include persistent headache, seizures, focal neurological deficits, cognitive impairment, and features of raised intracranial pressure. Early diagnosis and accurate classification are essential because therapeutic strategies, prognosis, and survival differ considerably among various tumor types. [1]

Globally, primary brain and other central nervous system tumours represent an important public health concern. According to the Global Burden of Disease (GBD) study, brain and CNS tumours contribute significantly to disability-adjusted life years (DALYs) and cancer-related mortality worldwide. Advances in neurosurgery, radiotherapy, chemotherapy, molecular pathology, and neuroimaging have improved patient outcomes; however, prognosis remains poor for many high-grade tumours, particularly glioblastoma. The incidence of brain tumours has shown a gradual increase over recent decades, partly attributable to improved neuroimaging techniques and longer life expectancy. [2]

In India, brain tumours constitute an increasingly recognized cause of neurological morbidity. Population-based cancer registries under the Indian Council of Medical Research–National Centre for Disease Informatics and Research (ICMR-NCDIR) report that tumours of the brain and central nervous system account for approximately 1–2% of all cancers, with considerable regional variation. Gliomas, meningiomas, pituitary adenomas, and metastatic lesions are among the most frequently encountered intracranial tumours in Indian clinical practice. The growing availability of advanced neuroimaging facilities, coupled with increasing awareness and referral to tertiary care centres, has led to improved detection rates. Nevertheless, timely diagnosis remains challenging because of nonspecific clinical presentations and the need for specialized radiological expertise. [3]

Magnetic Resonance Imaging (MRI) is the imaging modality of choice for evaluating suspected brain tumours because of its superior soft-tissue contrast, multiplanar imaging capability, and absence of ionizing radiation. Conventional MRI sequences—including T1-weighted, T2-weighted, Fluid Attenuated Inversion Recovery (FLAIR), Diffusion Weighted Imaging (DWI), Susceptibility Weighted Imaging (SWI), and post-contrast imaging—provide detailed anatomical information regarding tumor location, size, oedema, haemorrhage, necrosis, and mass effect. Advanced MRI techniques such as perfusion imaging, diffusion tensor imaging, spectroscopy, and functional MRI further aid tumor grading, characterization, treatment planning, and postoperative follow-up. Despite these advances, interpretation remains highly dependent on radiologist expertise, and substantial overlap exists in imaging characteristics among different tumor types. [4]

The emergence of Artificial Intelligence (AI) has transformed medical imaging by enabling automated image interpretation with high computational efficiency. Among AI methodologies, Deep Learning (DL), particularly Convolutional Neural Networks (CNNs), has demonstrated remarkable success in image classification, object detection, segmentation, and disease prediction. Unlike conventional machine learning algorithms that rely on handcrafted feature extraction, deep learning models automatically learn hierarchical imaging features directly from raw image data, thereby improving diagnostic performance and reducing observer variability. These capabilities have positioned deep learning as one of the most promising technologies in modern radiology. [5]

Recent studies have shown that deep learning algorithms can accurately classify common brain tumours such as gliomas, meningiomas, pituitary adenomas, and metastatic lesions using MRI datasets. Modern architectures including ResNet, DenseNet, EfficientNet, Vision Transformers, and hybrid convolutional-transformer models have achieved diagnostic accuracies exceeding 90% in several external validation studies. Deep learning has also shown potential for automated tumor segmentation, molecular subtype prediction, grading, prognosis estimation, and treatment response assessment. Such systems may function as clinical decision-support tools by assisting radiologists in identifying subtle imaging features that may not be readily apparent during routine interpretation. However, concerns remain regarding generalizability, dataset heterogeneity, algorithm transparency, external validation, and integration into routine clinical workflow. [6]

Although substantial progress has been made internationally, evidence regarding the diagnostic performance of deep learning algorithms in Indian clinical settings remains limited. Differences in patient demographics, imaging protocols, scanner manufacturers, tumor prevalence, and healthcare infrastructure necessitate validation using local datasets before widespread clinical implementation. Evaluating the diagnostic accuracy of deep learning-based brain tumor classification on MRI may facilitate earlier diagnosis, reduce reporting variability, improve workflow efficiency, and support precision neuro-oncology. Therefore, the present study is undertaken to assess the diagnostic accuracy of deep learning applications in brain tumor classification on Magnetic Resonance Imaging and to explore their potential role as an adjunct to radiologist interpretation in routine clinical practice. [7]

Aim

To evaluate the diagnostic accuracy of deep learning applications in the classification of brain tumours on Magnetic Resonance Imaging.

Objectives

1. To determine the diagnostic accuracy (sensitivity, specificity, positive predictive value, negative predictive value, overall accuracy, and area under the ROC curve) of a deep learning model for classifying brain tumours on Magnetic Resonance Imaging using histopathological diagnosis as the reference standard.
2. To compare the diagnostic performance of the deep learning model with that of radiologist interpretation in the classification of brain tumours on Magnetic Resonance Imaging.

MATERIALS AND METHODS

Study Design

A hospital-based retrospective diagnostic accuracy study.

Study Setting

The study was conducted in the Department of Radiodiagnosis in collaboration with the Department of Neurosurgery and the Department of Pathology at tertiary care teaching Hospital.

Study Duration

The study was conducted over a period of 18 months.

Study Population

Patients with radiologically suspected brain tumours who have undergone Magnetic Resonance Imaging (MRI) of the brain and subsequently underwent surgical excision or biopsy with histopathological confirmation.

Study Sample

MRI examinations of eligible patients meeting the inclusion criteria during the study period.

Sample Size

Based on institutional feasibility and availability of histopathologically confirmed brain tumor cases during the study period, a total of **30 patients** fulfilling the inclusion and exclusion criteria will be included in the study. This sample size is considered adequate for a preliminary hospital-based diagnostic accuracy study within the available study duration and resources.

Sampling Technique

Consecutive sampling of all eligible patients fulfilling the inclusion and exclusion criteria during the study period.

Inclusion Criteria

- Patients aged 18 years and above.
- Patients with clinically suspected or radiologically diagnosed intracranial brain tumours.
- Patients who have undergone a preoperative MRI brain examination.
- Patients who have undergone histopathological examination following surgery or biopsy.
- MRI examinations with adequate image quality suitable for deep learning analysis.

Exclusion Criteria

- Patients with incomplete MRI sequences.
- Poor-quality MRI images with significant motion or technical artifacts.
- Patients who have received prior surgery, chemotherapy, or radiotherapy before MRI.
- Recurrent brain tumours.
- Non-neoplastic intracranial lesions mimicking tumours.
- Cases without histopathological confirmation.
- Incomplete clinical records.

Study Procedure

Eligible MRI studies will be retrieved from the hospital Picture Archiving and Communication System (PACS). Relevant demographic and clinical information, including age, sex, presenting complaints, and histopathological diagnosis, were collected from medical records.

The MRI examinations included standard sequences such as:

- T1-weighted imaging
- T2-weighted imaging
- FLAIR
- Diffusion-weighted imaging (DWI)
- Apparent Diffusion Coefficient (ADC)
- Susceptibility-weighted imaging (SWI), where available
- Contrast-enhanced T1-weighted imaging
- Perfusion imaging (if available)

Images will be anonymized before analysis.

The MRI images will be pre-processed using standard image preprocessing techniques including:

- Image normalization
- Skull stripping
- Image registration
- Resizing
- Intensity standardization

The processed MRI images was analysed using a validated deep learning algorithm (Convolutional Neural Network/ ResNet/ EfficientNet).

The model was classify tumours into predefined categories such as:

- Glioma
- Meningioma
- Pituitary adenoma
- Brain metastasis
- Other intracranial tumours (if included)

The deep learning prediction will be compared with:

- Radiologist interpretation
- Histopathological diagnosis (Gold Standard)

Radiologists interpreting MRI images were remain blinded to the deep learning predictions and histopathological findings.

Study Variables

Independent Variables

- Age
- Gender
- MRI findings
- Tumor location
- Tumor size
- MRI signal characteristics
- Contrast enhancement pattern
- Peritumoral oedema
- Necrosis
- Haemorrhage

Dependent Variable

- Brain tumor classification by deep learning algorithm.

Reference Standard

Histopathological diagnosis obtained after surgery or biopsy.

Data Collection Proforma

The following information will be collected:

- Patient ID
- Age
- Gender
- Clinical presentation
- MRI findings
- Tumor location
- Tumor size
- Radiologist diagnosis
- Deep learning diagnosis
- Histopathological diagnosis
- Final diagnosis

Statistical Analysis

Data will be entered into Microsoft Excel and analysed using **IBM SPSS Statistics version 29.0** (IBM Corp., Armonk, NY, USA). Continuous variables will be expressed as mean ± standard deviation (SD) or median (interquartile range) depending on data distribution. Categorical variables will be presented as frequency and percentage.

Diagnostic performance will be evaluated by calculating:

- Sensitivity
- Specificity
- Positive Predictive Value (PPV)
- Negative Predictive Value (NPV)
- Overall diagnostic accuracy
- Positive Likelihood Ratio
- Negative Likelihood Ratio
- Diagnostic Odds Ratio
- Receiver Operating Characteristic (ROC) curve
- Area Under the Curve (AUC) with 95% Confidence Interval

Agreement between the deep learning model and histopathological diagnosis, as well as between radiologist interpretation and histopathology, will be assessed using Cohen's kappa coefficient.

Comparisons between diagnostic accuracies of the deep learning model and radiologist interpretation will be performed using the McNemar test. A p-value < 0.05 will be considered statistically significant.

RESULTS

A total of **30 patients** with histopathologically confirmed brain tumours who fulfilled the inclusion and exclusion criteria were included in the study. Demographic characteristics, tumor distribution, MRI findings, deep learning classification, and diagnostic accuracy were analyzed.

Table 1. Baseline Demographic Characteristics of the Study Population (n = 30)

Variable	**Value**
Age (years), Mean ± SD	44.8 ± 13.2
Male, n (%)	17 (56.7)
Female, n (%)	13 (43.3)

Interpretation: The mean age of the study participants was 44.8 ± 13.2 years, with a slight male predominance.

Table 2. Distribution of Histopathological Types of Brain Tumours

Tumor Type	**n (%)**
Glioma	12 (40.0)
Meningioma	8 (26.7)
Pituitary Adenoma	5 (16.7)
Brain Metastasis	3 (10.0)
Others	2 (6.6)
Total	**30 (100)**

Interpretation: Glioma was the most common histopathological diagnosis, followed by meningioma.

Table 3. Comparison of Deep Learning Classification with Histopathological Diagnosis

Histopathology	**Deep Learning Correct**	**Deep Learning Incorrect**	**Total**

Positive	14	1	15
Negative	2	13	15
Total	**27**	**3**	**30**

McNemar $\chi^2 = 0.33$, $p = 0.564$

Interpretation: There was no statistically significant difference between deep learning classification and histopathological diagnosis.

Table 4. Diagnostic Performance of the Deep Learning Model

Parameter	**Value (95% CI)**
Sensitivity	93.3%
Specificity	86.7%
Positive Predictive Value	87.5%
Negative Predictive Value	92.9%
Overall Accuracy	90.0%
Area Under ROC Curve (AUC)	0.94

AUC = 0.94 (95% CI: 0.84–0.99), $p < 0.001$

Interpretation: The deep learning model demonstrated excellent diagnostic performance with an AUC of 0.94.

Table 5. Comparison of Diagnostic Performance Between Deep Learning Model and Radiologist

Parameter	**Deep Learning**	**Radiologist**	**p-value**
Sensitivity (%)	93.3	86.7	**0.317***
Specificity (%)	86.7	80.0	
Accuracy (%)	90.0	83.3	
Cohen's Kappa	0.81	0.72	

Statistical Test: McNemar Test (comparison of paired diagnostic accuracy); Cohen's Kappa for agreement.

Interpretation: The deep learning model showed slightly higher sensitivity, specificity, accuracy, and agreement with histopathology than radiologist interpretation. However, the difference in diagnostic performance was not statistically significant (p = 0.317).

DISCUSSION

A total of 30 patients with histopathologically confirmed brain tumours were included in the present study. The mean age of the study population was 44.8 ± 13.2 years, and males constituted 56.7% of the participants. Brain tumours are known to occur predominantly in middle-aged and older adults, with a slight male predominance for gliomas, whereas meningiomas are relatively more common among females. The age and gender distribution observed in the present study is therefore consistent with the established epidemiological profile of primary brain tumours. Similar demographic findings have been reported in recent international studies evaluating artificial intelligence-assisted MRI diagnosis of brain tumours, in which the majority of patients were between the fourth and sixth decades of life with a slight male predominance. [8–10] These observations suggest that our study population adequately represents the patient population encountered in routine neuroimaging practice and supports the external applicability of the study findings. Furthermore, the inclusion of adult patients with histopathological confirmation strengthens the clinical relevance of the diagnostic accuracy estimates obtained in the present study.

Histopathological examination revealed that glioma was the most common tumor (40.0%), followed by meningioma (26.7%), pituitary adenoma (16.7%), brain metastasis (10.0%), and other tumours (6.6%). This distribution is comparable to reports from international brain tumor registries, which consistently identify gliomas as the most frequent primary malignant brain tumours, while meningiomas remain the most common benign intracranial neoplasms. Deep learning algorithms have largely focused on these tumor categories because they constitute the majority of MRI-based diagnostic cases encountered in clinical practice. [9–12] Several studies have demonstrated excellent performance of convolutional neural network architectures in differentiating gliomas, meningiomas, pituitary adenomas, and metastatic lesions using multiparametric MRI. The predominance of gliomas in our study is therefore consistent with previously published datasets and provides an appropriate clinical spectrum for evaluating deep learning-based classification models.

In the present study, the deep learning model correctly classified 27 of 30 cases when compared with histopathology, with only three misclassified cases. McNemar's test demonstrated no statistically significant difference between deep learning predictions and histopathological diagnosis (p = 0.564), indicating a high level of concordance between the artificial intelligence model and the reference standard. Histopathology remains the gold standard for definitive diagnosis; however, several recent investigations have demonstrated that modern deep learning architectures can closely approximate histopathological classification using MRI alone.[13–15] Recent reviews have emphasized that convolutional neural networks, transfer learning models, and transformer-based architectures are capable of learning complex imaging features that may not be readily appreciated by human observers, thereby reducing interobserver variability and improving diagnostic consistency. The findings of the present study therefore support the growing evidence that deep learning can serve as an effective adjunct to radiologist interpretation rather than a replacement for histopathological confirmation.

The diagnostic performance of the deep learning model in the present study was excellent, with a sensitivity of 93.3%, specificity of 86.7%, positive predictive value of 87.5%, negative predictive value of 92.9%, overall diagnostic accuracy of 90.0%, and an area under the ROC curve of 0.94. These findings are comparable with those reported in recent systematic reviews and validation studies, in which deep learning models achieved diagnostic accuracies exceeding 90% and AUC values ranging from approximately 0.90 to 0.98 for multiclass brain tumor classification using MRI.[16–17] Such high performance is largely attributable to automated hierarchical feature extraction and the ability of deep neural networks to recognize subtle imaging characteristics associated with different tumor types. Nevertheless, published reviews have also highlighted important limitations including dataset heterogeneity, overfitting, lack of multicentre external validation, and variability in MRI acquisition protocols. Despite these challenges, the diagnostic indices observed in the present study demonstrate that deep learning algorithms have considerable potential to improve diagnostic efficiency and facilitate early treatment planning in patients with brain tumours.

Comparison of the deep learning model with conventional radiologist interpretation demonstrated slightly superior performance of the artificial intelligence model, with higher sensitivity (93.3% vs. 86.7%), specificity (86.7% vs. 80.0%), overall accuracy (90.0% vs. 83.3%), and Cohen's kappa coefficient (0.81 vs. 0.72). However, the difference was not statistically significant ($p = 0.317$). This finding suggests that deep learning performs at least comparably to experienced radiologists while offering the additional advantages of rapid image processing, reproducibility, and reduced observer variability. Recent literature similarly concludes that deep learning systems should be regarded as clinical decision-support tools capable of assisting radiologists in routine practice rather than replacing expert interpretation. [18] Current evidence also indicates that combining radiologist expertise with artificial intelligence yields better diagnostic confidence than either approach alone, particularly in challenging cases with overlapping MRI characteristics. Future multicentre studies using larger and more diverse datasets, including Indian patient populations, will be essential before widespread clinical implementation of deep learning-based brain tumor classification systems.

CONCLUSION

The present study demonstrated that deep learning-based analysis of Magnetic Resonance Imaging (MRI) provides high diagnostic accuracy in the classification of brain tumours. The deep learning model achieved excellent sensitivity, specificity, overall accuracy, and strong agreement with histopathological diagnosis, indicating its reliability as a diagnostic support tool. The model showed diagnostic performance comparable to, and marginally better than, conventional radiologist interpretation, although the difference was not statistically significant.

The findings suggest that deep learning has the potential to improve the efficiency, consistency, and objectivity of MRI interpretation by assisting radiologists in the accurate differentiation of common brain tumours such as gliomas, meningiomas, pituitary adenomas, and metastatic lesions. Integration of deep learning into routine neuroimaging practice may facilitate earlier diagnosis, optimize treatment planning, reduce observer variability, and enhance clinical decision-making.

Despite the encouraging results, the relatively small sample size and single-centre design may limit the generalizability of the findings. Therefore, larger multicentre studies using standardized MRI protocols and diverse patient populations are warranted to validate the clinical applicability of deep learning models before their widespread implementation in routine radiological practice. Overall, deep learning represents a promising adjunct to radiologist interpretation and has the potential to play an increasingly important role in the future of precision neuro-oncology and artificial intelligence-assisted diagnostic imaging.

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