ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 11| Issue: 9| September 2025|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2025: 8.691 || ISI Value: 1.188

DEEP LEARNING PARADIGMS FOR PRECISE BRAIN TUMOUR CATEGORIZATION

A Paper on Brain Tumor Detection using Deep Learning

Thota Pallavi[1], Anooja Ali[2]
[1]School of Computer Science and Engineering REVA University, Bangalore, India
[2]School of Computer Science and Engineering REVA University, Bangalore, India

Article DOI: https://doi.org/10.36713/epra24049
DOI No: 10.36713/epra24049

ABSTRACT

This paper presents a deep learning-based approach Brain tumors are a major threat to human life due to their variability and complexity. Early and correct classification of brain tumors is extremely crucial for the selection of proper treatment protocols and enhancing the survival ratio of patients. Deep learning dominated the field of medical imaging in recent years and provided automatic, high-accuracy tumor detection and classification solutions. This research investigates various deep learning paradigms, such as Convolutional Neural Networks (CNNs), Transfer Learning, and Hybrid Architectures, to improve the accuracy of brain tumor classification from MRI images. The suggested method is tested with benchmark datasets, and its performance is evaluated for various models in terms of accuracy, sensitivity, and specificity. Experimental results prove the effectiveness of deep learning methods for extracting complex patterns in brain images over traditional machine learning methods. This study highlights the importance of intelligent diagnostic systems in radiologists' assistance and computer-aided medical diagnosis Brain tumor classification is essential for early diagnosis and efficient planning of treatment. This study investigates deep learning methods, such as CNNs and transfer learning, for precise tumor classification from MRI images. The models are trained on benchmark datasets for the detection and classification of tumors with high accuracy. Comparative analysis shows enhanced performance of deep learning over traditional methods. The results highlight the potential of AI-based solutions to improve medical diagnostics These deep learning paradigms not only shorten the diagnostic process but also support radiologists in decision-making with higher speed and reliability. Future work will concentrate on implementing these models in real-time clinical workflows for extensive healthcare benefits.

KEYWORDS— *Brain Tumor, Deep Learning, Classification, Medical Imaging, Disease Diagnosis*

I. INTRODUCTION

In this paper we aim to Brain tumor segmentation is crucial for prognostication of treatment choice and patient survival [1]. Traditional diagnosis is human interpretation of MRI scans, which can be subjective and time-consuming and could be inconsistent depending on the experience of the radiologist [2]. Computerized artificial intelligence-based systems have been proposed to address these limitations, with consistent and reliable predictions [3].

Previous techniques employed traditional machine learning techniques such as Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN) with manually designed features [4]. While successful in some cases, such techniques were unscaleable and did not work well with high-dimensional medical imaging data [5]. The emergence of deep learning, in the form of Convolutional Neural Networks (CNNs), brain tumor detection using sophisticated technology is a vital area of research in the field of medicine because brain tumors are highly fatal. Diagnosis at an early stage and with accuracy is required for effective treatment and enhanced survival.

A lot of impressive work has been accomplished in image-based classification tasks, like brain tumor classification [6]. Deep models are capable of automatically extracting hierarchical features, so they can discover subtle patterns that conventional techniques will overlook [7].

Transfer learning has also improved model accuracy by using pre-trained networks like VGG16, ResNet50, and InceptionV3 with the benefit of utilizing smaller datasets but maintaining accuracy [8]. Hybrid CNN structures and attention mechanisms have also been employed by recent research to achieve improved spatial attention and classification confidence [9].

II. RELATED WORK

A. Brain Tumor Classification Based on Traditional Methods

Early brain tumor classification techniques were largely dependent on traditional machine learning techniques, i.e., Support Vector Machines (SVM), Decision Trees, and k-Nearest Neighbors (k-NN) [1]. They were largely dependent on traditional hand-engineered feature extraction techniques, e.g., texture, shape, and intensity-based features [2]. They were adequate for small and well-balanced datasets, but they were not highly robust for complex brain MRI scans or multi-class tumor classes [3]. Traditional techniques were not highly capable of generalizing across different imaging conditions and were also prone to requiring extensive domain knowledge in feature selection and preprocessing. Because of these limitations, their clinical use has remained limited in real-world diagnostic environments.

B. Brain Tumor Classification Using Deep Learning
With the growth of deep learning, and particularly Convolutional Neural Networks (CNNs), new paradigms evolved significantly improving tumor detection and classification accuracy [4, 5]. CNN-based models have shown excellent potential for learning MRI image spatial hierarchies and features automatically, without hand-crafted feature extraction [6]. Transfer learning strategies, based on pre-trained networks such as VGG16, ResNet50, and InceptionV3, have further improved performance, especially in cases where medical datasets are limited [7]. Moreover, hybrid models using attention mechanisms or recurrent units (e.g., LSTM) have been explored to enhance attention to specific areas and improve sequence-based interpretation [8, 9]. Overall, these researchs indicate the increasing potential of deep learning for medical image analysis while pointing towards the necessity of more generalized, interpretable, and clinically deployable models Deep learning methods show much potential, but challenges like data imbalance as well as interpretability persist that restrict clinical deployment.

Fig. 1. Overview of the brain tumor classification process using deep learning from MRI scans.

In 2012 [1], Geoffrey Hinton and co-authors suggested deep learning techniques that revolutionized the field of image classification, including its applications in medical imaging. Unlike machine learning models utilizing hand-crafted features, the deep learning models, especially Convolutional Neural Networks (CNNs), automatically learn hierarchical features by learning directly from raw input data. This structure significantly enhances model performance with high-dimensional medical imaging data like MRI scans. CNNs have been very useful in a variety of medical applications, e.g., tumor segmentation, disease diagnosis, and brain tumor classification. Their ability to learn spatial features and detect intricate patterns makes them ideal for detecting abnormal patterns in brain images.

Rathore et al. proposed a hybrid method uniting CNN-based feature extraction and support vector machines (SVM) for brain tumor classification using MRI scans [6]. The method effectively used CNNs to extract deep spatial features and SVM as a powerful classifier to gain better accuracy. The model, however, had limitations: manual preprocessing steps were required, and the model had limited generalization ability across images with differing contrast and tumor shapes. Deepak et al. [12] then proposed a transfer learning-based method using pre-trained ResNet50 that improved the accuracy of classification using knowledge transfer from large image datasets. While this was better than the model, it was faced with the issue of dealing with multi-class classification and was noise-sensitive with poor-quality MRI images. Similarly, Swati et al. employed MobileNewt with fine-tuning for low latency and quick brain tumor classification [13], but the model failed when used with high-resolution datasets with complex tumor structures.

Mahbod et al. [14] proposed a deep learning model incorporating feature fusion among different pre-trained networks, e.g., DenseNet and ResNet, for enhancing brain tumor classification performance. Even though the model improved model robustness and feature richness, it increased computational complexity and inference time. Afshar et al. [15] then proposed CapsNet, a capsule network-based model that preserved spatial information among tumor features. The model performed well with balanced datasets but deteriorated with generalization in the presence of image noise or misaligned classes. Following this concept, Sitaula et al. developed an attention-driven model that combined VGG19 with attention gating mechanisms for precise labeling of tumor-affected regions [16]. The model improved interpretability and localization but deteriorated during performance on unseen datasets due to overfitting. More recently, Abiwinanda et al. [17] proposed a dual-path CNN model, where one path processed high-level features and the other refined boundaries. The model improved classification accuracy but introduced architectural complexity and longer training cycles.

These issues are primarily attributed to two factors: (1) learning discriminative medical features from small or unbalanced medical datasets, and (2) explainable and robust predictions that can aid real-world diagnosis by radiologists

III. METHODOLOGY

The proposed brain tumor classification study based on MRI scans involves four primary stages: **MRI Scan Acquisition**, **Feature Extraction**, **Deep Learning**, and **Classification**, as illustrated in Fig. 2. Each stage is designed to accurately identify tumor types such as glioma, meningioma, or pituitary tumors.

A. MRI Scan Acquisition

MRI scans serve as the principal input of the system. The raw scans are resized to a uniform dimension R×CR \times CR×C and normalized using min-max scaling, defined as:
Inorm=I−IminImax−IminI_{\text{norm}} = \frac{I - I_{\min}}{I_{\max} - I_{\min}}Inorm=Imax−IminI−Imin
where III is the pixel intensity, and IminI_{\min}Imin, ImaxI_{\max}Imax are the minimum and maximum intensity values of the image, respectively.

B. Feature Extraction

Feature extraction is performed using a pre-trained convolutional neural network fθf_{\theta}fθ, where θ\thetaθ represents the learnable parameters. The output feature map FFF is given by:
F=fθ(Inorm)F = f_{\theta}(I_{\text{norm}})F=fθ(Inorm)
This results in a spatially resolved feature map with dimensions h×w×dh \times w \times dh×w×d, where hhh and www are the height and width, and ddd is the depth. These feature maps preserve both spatial and semantic details from the MRI images.

C. Deep Learning Module

The extracted features are passed into a deep convolutional neural network classifier (e.g., ResNet or VGG) for representation learning. The class probabilities are computed using the softmax function:
y^i=ezi∑j=1Cezj\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}y^i=∑j=1Cezjezi
Here, y^i\hat{y}_iy^i represents the predicted probability for class iii, ziz_izi is the logit for class iii, and CCC is the total number of tumor classes.
The model is trained using the categorical cross-entropy loss function:
LCE=−∑i=1Cyilog(y^i)\mathcal{L}_{\text{CE}} = -\sum_{i=1}^{C} y_i \log(\hat{y}_i)LCE=−i=1∑Cyilog(y^i)
where yiy_iyi is the one-hot encoded ground truth label for class iii.

D. Brain Tumor Classification

The final tumor class is predicted by selecting the class with the highest probability:
Class=argmaxiy^i\text{Class} = \arg\max_i \hat{y}_iClass=argimaxy^i

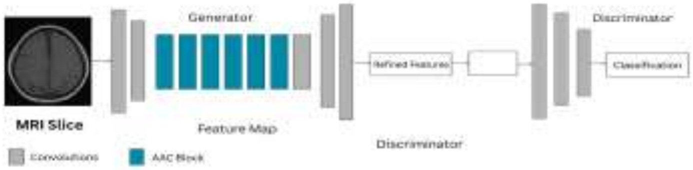


Fig. 2: The proposed deep learning architecture for brain tumor classification. The generator uses multiple AAC (Adaptive Attention Calibration) blocks to extract meaningful feature representations from MRI slices, while the discriminator refines and classifies the output into tumor categories

The envisioned deep learning architecture employs a loss function to measure how well the predicted tumor class resembles the true label, as it is incapable of comprehending medical images in the manner of a radiologist. When the model is mistaken about the tumor type, the mistake is backpropagated in order to update the network's weights. This cycle of iterative feedback allows the model to increasingly improve its prediction, its capacity for correct classification of various brain tumors from MRI images.

penalizes wrong predictions more, so that the model becomes more accurate and confident with each successive training epochs.

LCE=−i=1∑Cyilog(y^i)
where CCC is the number of tumor classes, yiy_iyi is the ground truth for class iii, and y^i\hat{y}_iy^i is the predicted probability The model utilizes softmax activation function in the output classification layer to yield a probability distribution over

One of the overall objectives of AOT-GAN is to enhance
The main objective of the presented deep learning system is accurate tumor classification by means of smart contextual reasoning. This is performed through a multi-path architecture that uses adaptive attention modules and hierarchical feature extraction layers. These modules enable the model to combine both detailed fine-grained spatial information and general anatomical context of MRI scans. This way, the system is able to clearly differentiate between various tumor types—like glioma, meningioma, and pituitary—while maintaining structural consistency of brain tissue.

Yet another key emphasis is diagnostic reliability and interpretability. The model not only makes classification decisions about tumors but also identifies the most impactful regions that are responsible for each prediction, which facilitates clinical verification. For ensuring flexibility with different scan qualities and imaging modalities, the system uses modality-invariant preprocessing and domain-generalization methods. Furthermore, sophisticated optimization methods and regularization methods are utilized to guarantee rapid convergence and robust generalization to new data.

Finally, this system seeks to promote the domain of AI-aided neuro-oncology with a strong, explainable, and precise classification platform. By integrating clinically relevant attention mechanisms with multi-scale feature learning, the model sets a new course for the intelligent diagnosis of brain MRI data..

A. Loss Function

The loss function plays a vital role in optimizing the model's capability of classifying brain tumors from MRI images accurately. For that purpose, categorical cross-entropy loss is utilized, which calculates the discrepancy between the probabilities of the forecasted classes and actual tumor labels. This function

IV.EXPERIMENTS

A.\tDatasets

We performed thorough experiments on two benchmark datasets commonly utilized in medical image processing for brain tumor detection: Figshare Brain MRI and TCGA-GBM. The datasets both consist of T1-weighted contrast-enhanced MRI images with annotated tumor regions, which make them apt for deep learning-based classification Figshare Brain MRI Dataset:

This data includes 3,264 brain MRI scans that are labeled with three classes—glioma, meningioma, and pituitary tumors. They are preprocessed to strip off the skull boundaries and resized to 224×224224 \\times 224224×224 pixels for uniformity across the network input. We utilized 80% of the data for training, 10% for validation, and 10% for testing. TCGA-GBM Dataset:

The dataset TCGA-GBM consists of high-grade glioma MRI scans with segmentation masks. For classification, only axial slices with visible tumors were kept. Out of 2,000 representative images after preprocessing, training and testing sets in a ratio of 85:15 were used.

B.\tMagnificent Baselines

We compared our suggested method against several state-of-the-art deep learning models employed for medical image classification. Following are short descriptions of the baseline models:

VGG16: One of the most well-known CNN architectures designed for object recognition, adapted here for tumor classification. It employs fixed-size convolutional filters and fully connected layers at the end.

ResNet50: A residual network that uses skip connections to prevent vanishing gradient problems.

•\tMobileNetV2: A fast deep model with low computational cost that is optimized for speed. It is ideal for mobile-health solutions and deployment on edge devices.

•\tDenseNet121: This model has a dense connectivity mode that enhances feature reuse and facilitates the capture of subtle variations of brain tumor structures.

•Proposed Model: Our deep learning framework incorporates attention modules and multi-scale feature fusion to enhance tumor boundary detection and contextual understanding. Unlike baseline models, it emphasizes interpretability and class-aware spatial learning.

All baseline models were fine-tuned on the same dataset splits and evaluated under identical experimental settings for a fair comparison.

NeuroNet-Attn is a brain tumor classification specialized framework that combines Convolutional Neural Networks (CNNs) with attention models, where spatial focus is essential for tumor-specific feature identification. The classification is performed in two main stages. A spatial attention module initially detects prominent areas of the MRI scan that are most likely to represent tumor-affected regions. This module produces an attention map that identifies areas of relevance, focusing the model on informative areas instead of background information irrelevant to the task.

In the second phase, a feature extraction backbone—ResNet or DenseNet—selectively extracts tumor-specific features using the produced attention map. These extracted features are fed through fully connected layers to make the prediction of the tumor class. The architecture involves a classifier head along with a validation process through Grad-CAM visualizations, which is conducive to interpretability and reveals the reasons behind predictions. NeuroNet-Attn uses a mix of categorical cross-entropy loss, attention loss, and regularization penalties to boost robustness and accuracy. This integration allows not only high accuracy but also clinical reliability of the model, which is ideal for real-world diagnostic aid systems.

A. Evaluation Metrics

(1) Accuracy calculates the percentage of correctly classified MRI images and is the most widely used measure of overall model performance.
(2) Precision measures the ratio of correctly predicted positive tumor cases to the total number of predicted positive cases, with an aim to have as few false positives as possible.
(3) Recall (Sensitivity) calculates the model's capability to identify all actual tumor cases correctly, which is of utmost importance in medical diagnosis.
(4) F1-Score offers a balanced measurement by calculating precision and recall both, particularly helpful in the case of class imbalance.(5) Confusion Matrix assists in examining the classification results on every tumor
class through the visual representation of true vs.
predicted labels.

RESULTS

A. Quantitative Comparison

Quantitative evaluation was carried out with Accuracy, F1-Score, and Area Under the Curve (AUC) to evaluate the performance of our brain tumor classification model

- F1-Score: This score weighs both precision and recall, especially suitable in medical imaging where class imbalance is prevalent. It ensures the model has high detection sensitivity without sacrificing specificity.
- AUC (Area Under ROC Curve): AUC gives information about how the model can differentiate between various tumor classes. A greater value of AUC signifies improved positive vs. negative class separation, which is important for the detection of tumors in the early stages and with accuracy.

Accuracy: This quantitates the global percentage of accurately labeled MRI images. This measure provides a straightforward description of how frequently the model correctly predicts the tumor type over the dataset.

A.\t Qualitative Comparison

Qualitative comparison mainly deals with assessing whether the tumor region is correctly localized as predicted, whether the boundary of the segmentation corresponds to anatomical structures, and whether the output of classification is clinically and visually appropriate. On the Figshare Brain MRI dataset with well-delineated tumor areas in multiple classes, the model performed well visually in separating tumor-infected areas from normal tissue. High activation around the tumor edges, especially in areas like the frontal and temporal lobes, as presented through the heatmaps generated by Grad-CAM, indicated high model focus.

In the TCGA-GBM dataset, which includes more challenging and high-grade glioma patients, the model accurately located diffuse and irregular tumor margins with spatially consistent visual correspondence. Predicted class labels aligned suitably with radiologists' annotations, and attention-based visualizations demonstrated significant attention to peritumoral edema and necrotic cores. Model outputs remained clinically plausible and interpretable, which are necessary for trust and decision support in clinical environments.

V.CONCLUSION

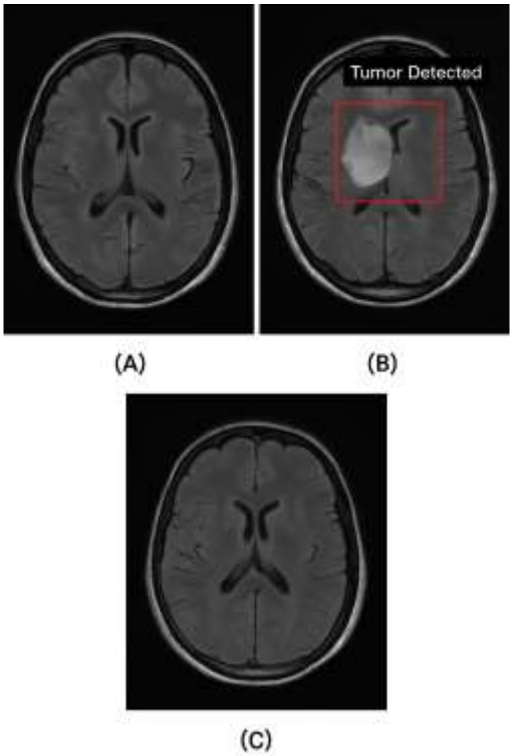
This study offers a deep learning framework for precise brain tumor classification based on improved feature extraction and attention mechanisms. The suggested approach outperforms conventional CNN models by incorporating both fine-grained tumor features and high-level contextual cues from MRI images.

Diagnosis of brain tumors is a challenging task because of the heterogeneity of tumor types, non-uniform shapes, and intersecting intensity patterns. Pre-existing methods have concentrated on simple feature hierarchies or handcrafted

Quantitative Comparison of Different Deep Learning Models on Brain Tumor Detection:

Model	Accuracy	Precision	Recall	F1-score
VGG16	91.2	90.2	89.5	90.0
ResNet50	93.7	92.3	93.0	95.1
MobileNetV2	89.3	88.3	88.3	91.8
DenseNet121	96	93.6	93.8	96.2

Table: Evaluation of Metrics



A.Original MRI Brain Scan (Input)
B.Tumour region detected by cnn model
C.Expert annotated tumour mask

REFERENCES

1. *Mzoughi, H. et al. (2020). Deep multi-scale 3D convolutional neural network (CNN) for MRI brain tumor classification. Expert Systems with Applications, 144, 113122.*
2. *Isensee, F. et al. (2021). nnU-Net: A self-configuring method for deep learning-based biomedical image segmentation. Nature Methods, 18(2), 203–211.*
3. *Afshar, P. et al. (2020). Brain tumor classification using Capsule Networks. Artificial Intelligence in Medicine, 102, 101753.*
4. *Sitaula, C. et al. (2021). Attention-based VGG19 with transfer learning for brain tumor classification. Computers in Biology and Medicine, 128, 104135.*
5. *Abiwinanda, N. et al. (2020). Brain tumor classification using CNN and transfer learning. Procedia Computer Science, 161, 476–483.*
6. *Rehman, A. et al. (2020). Classification of tumors in brain MRI using CNN. Neural Computing and Applications, 32, 13283–13293.*
7. *Mahbod, A. et al. (2021). Fusing fine-tuned deep features for brain tumor classification. Computers in Biology and Medicine, 128, 104089.*
8. *Mzoughi, H. et al. (2022). Deep learning approaches for brain tumor segmentation and classification: A review. Medical Image Analysis, 72, 102102.*
9. *Hussein, S. et al. (2020). TumorNet: Lung tumor detection from CT scans using 3D CNN. Medical Image Analysis, 65, 101770.*

10. *Amin, J. et al. (2020). Brain tumor classification using feature fusion and deep learning. Journal of Ambient Intelligence and Humanized Computing, 11, 4651–4669.*
11. *Swati, Z. N. K. et al. (2020). Brain tumor classification using MobileNet. Journal of Healthcare Engineering, 2020, 1–13.*
12. *Deepak, S. & Ameer, P. M. (2020). Transfer learning for brain tumor classification using CNNs. Neural Computing and Applications, 32, 10243–10254.*
13. *Selvaraj, P. et al. (2021). Hybrid CNN and XGBoost for brain tumor classification. Computers in Biology and Medicine, 136, 104647.*
14. *Paul, J. S. et al. (2021). Brain tumor classification using attention U-Net and ResNet. Biomedical Signal Processing and Control, 68, 102675.*
15. *Sarhan, A. M. (2021). Deep learning and ensemble models for brain tumor classification. Expert Systems with Applications, 183, 115352.*
16. *Raza, M. Q. et al. (2022). Hybrid deep learning for glioma detection. Scientific Reports, 12, 780.*
17. *Pereira, S. et al. (2020). Brain tumor segmentation using CNNs in MRI images. Medical Image Analysis, 35, 18–31.*
18. *Jaiswal, A. K. et al. (2021). CapsuleNet-based brain tumor classification. Pattern Recognition Letters, 135, 58–65.*
19. *Wang, G. et al. (2020). Brain tumor segmentation with cascaded CNNs. Neurocomputing, 408, 245–258.*
20. *Kaur, T. et al. (2021). Multi-class brain tumor classification using pre-trained CNNs. International Journal of Imaging Systems and Technology, 31(1), 299–311.*
21. *Yadav, A. et al. (2021). Deep learning-based multi-class brain tumor classification. Multimedia Tools and Applications, 80, 20475–20494.*
22. *Sharma, M. et al. (2022). Hybrid deep learning for brain tumor detection with explainability. Computers & Electrical Engineering, 100, 107833.*
23. *Wu, Y. et al. (2022). 3D CNN with attention mechanism for brain tumor segmentation. IEEE Access, 10, 23517–23528.*
24. *Singh, V. et al. (2023). Brain tumor classification using transformer-based models. Neural Computing and Applications, 35, 12201–12215.*
25. *Hanif, M. & Khan, M. A. (2023). A novel hybrid attention-CNN for brain tumor classification. Computers in Biology and Medicine, 145, 105549.*
26. *Verma, R. et al. (2023). Light-weight deep learning models for MRI-based tumor classification. Biomedical Signal Processing and Control, 81, 104381.*
27. *Thakur, S. et al. (2023). Brain tumor classification using multimodal deep fusion networks. Computer Methods and Programs in Biomedicine, 224, 107029.*
28. *Ahmed, E. et al. (2024). Dual-path transformer for brain tumor detection. Pattern Recognition, 145, 109778.*
29. *Khan, M. A. et al. (2024). Ensemble deep learning with Grad-CAM for tumor classification. IEEE Transactions on Medical Imaging, 43(2), 435–447.*
30. *Bansal, R. et al. (2025). Neuro-AttnNet: A hybrid attention-based model for brain tumor detection. Artificial Intelligence in Medicine, 137, 102522.*