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BrainFusion: Deep Learning for Early Detection and Grading of Brain Tumors Using Medical Imaging and Clinical Data

Prathiba R[1], Dr. Sunitha B S[2]
[1]*Research Scholar, Department of Computer Science & Engineering, PES Institute of Technology and Management, Shimoga, Karnataka, India | Visvesvaraya Technological University, Belagavi, Karnataka, India*
prathibhar@sjcit.ac.in
[2]*Research Supervisor, Department of Computer Science Engineering (Data Science), PES Institute of Technology and Management, Shimoga Karnataka, India | Visvesvaraya Technological University, Belagavi, Karnataka, India*
sunitha.bs@pestrust.edu.in

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ABSTRACT

Brain tumors are still one of the most dangerous and deadly types of cancer. Early detection and correct grading are very important for effective treatment. This study presents a dual-stage artificial intelligence framework that utilizes advanced transformer-based deep learning architectures, specifically the Swin Transformer and Vision Transformer (ViT), for the early detection and grading of brain tumors through MRI images and clinical metadata. Our approach takes advantage of these transformer models' better feature extraction and contextual representation, which is not the case with traditional CNN-based methods. The framework consists of two core components: (1) a transformer-based classifier for detecting tumor presence in 2D MRI slices, and (2) a multimodal fusion model combining imaging features and clinical data (age, gender, tumor type, grade) to predict tumor grade (HGG vs LGG). We also made a web interface powered by Gradio that lets users upload images and get a diagnosis in real time. This makes the model available to both researchers and doctors. We use publicly available brain MRI datasets like BraTS and TCGA to create and test our model. show that the Swin Transformer is better than current CNN-based methods at finding tumors and classifying grades, with an accuracy of up to 98.3% and 95.2%, respectively. These findings validate the effectiveness and promise of transformer architectures and web-based AI tools in enhancing neuro-oncological diagnosis.

Keywords: Brain Tumor Detection; Swin Transformer; Vision Transformer; Deep Learning; MRI Classification; Tumor Grading; Multimodal Fusion; Clinical Metadata; Gradio Interface; Medical Imaging; Attention Mechanisms; CNN Baseline; Transformer Models; AI in Healthcare; Brain Tumor Segmentation

INTRODUCTION

Brain tumors, especially gliomas, are some of the most dangerous neurological disorders and are still a major problem in clinical oncology. Finding these tumors early and grading them correctly are very important for figuring out the prognosis and coming up with good treatment plans. Magnetic Resonance Imaging (MRI) is the best way to find brain tumors without having to cut into the body because it has high spatial resolution and contrast across soft tissues. However, interpreting MRI scans by hand is time-consuming, prone to differences between observers, and often not good enough to find small changes in early tumor growth. Automated brain tumor detection systems have grown quickly since deep learning, especially Convolutional Neural Networks (CNNs), became more popular. But these methods often have trouble getting long-range dependencies and contextual information from high-dimensional medical data.

Conventional CNN-based systems generally exhibit limitations in modeling global spatial relationships within image data and are additionally hindered by their ineffectiveness in integrating non-image clinical data. These limitations can lead to diminished sensitivity to early-stage tumors and subpar tumor grading efficacy. Furthermore, even though AI models have improved in research settings, they can't be used in the clinic very well because there aren't any easy-

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to-use interfaces for real-time diagnosis support.

To overcome these limitations, we propose a comprehensive and scalable deep learning framework that incorporates transformer-based architectures, specifically the Swin Transformer and Vision Transformer (ViT), to improve the detection and classification of brain tumors. These models, which were trained on large datasets and then fine-tuned on medical images, do a better job of capturing global features and fine-grained contextual cues than traditional CNNs. Our dual-stage system consists of (1) using Swin Transformer to find tumors in MRI slices and (2) using a combination of image embeddings and clinical metadata like age, gender, and survival indicators to grade tumors.

To connect research with real-world use, we added a Gradio-based web interface that lets users upload brain scans and get tumor predictions right away. This makes it easy and quick to use. The system has been tested on publicly available datasets like BraTS and TCGA, and it works better than anything else at finding tumors and predicting their grades. Recent studies have yielded encouraging outcomes employing deep learning in the analysis of brain tumors. Our work fills this gap by combining cutting-edge models with a web tool that can be used in real life to make them more clinically relevant.

LITERATURE REVIEW

Recent developments in deep learning have greatly enhanced the detection of brain tumors via medical imaging, especially magnetic resonance imaging (MRI). Different methods have been tried that use convolutional neural networks (CNNs), transfer learning, and explainable AI.

Rahman et al. [1] proposed a hybrid methodology that combines CNNs with Local Binary Patterns (LBP) and explainable AI techniques such as SHAP to enhance interpretability and diagnostic efficacy. In the same way, Alnageeb and Supriya [2] came up with a lightweight MK-YOLOv8 model that uses Ghost Convolutions to find small brain tumors with high accuracy on the Br35H dataset.
Wong et al. [3] demonstrated a classification accuracy of 99.24% utilizing a fine-tuned VGG16 CNN trained on more than 17,000 MRI images, illustrating the efficacy of transfer learning and data augmentation in enhancing model performance. Lu et al. [4] proposed an additional CNN-based method that integrates various MRI modalities into RGB-like images, utilizing Darknet53 for classification and ResNet50 for segmentation.

To improve interpretability, Iftikhar et al. [5] made a minimal-layer CNN architecture that used Gradient-weighted Class Activation Mapping (Grad-CAM) and LIME. Vasavan et al. [6] and Vengatesh et al. [7] integrated CNNs with MobileNetV2 and MLP for early detection utilizing a Kaggle-based dataset, attaining 97% accuracy.

Velpula et al. [8] investigated hyperparameter tuning and ensemble techniques that integrate deep learning and machine learning to achieve optimal classification. Puttegowda et al. [9] also looked at different machine learning algorithms, such as Random Forest and Logistic Regression, that were trained on a balanced set of 3000 MRI images.

Singh et al. [10] assessed CNN-based multi-class classification on a labeled dataset utilizing DenseNet169 and VGG19, indicating elevated accuracy. Ganesh et al. [11] showed that VGG16-based segmentation methods work very well.

Several studies, including Gupta et al. [12] and Kumar et al. [13], employed transfer learning and optimization techniques to decrease computational load while preserving accuracy. Hashemzehi et al. [14] put forward a hybrid CNN model that uses NADE to find tumors with great sensitivity.

Hosny et al. [15] and Tampu et al. [16] investigated ensemble learning and age-fusion methodologies in vision transformers, demonstrating enhanced classification accuracy in pediatric brain tumors.

Smitha et al. [17] employed deep learning for early-stage classification, incorporating data preprocessing to enhance accuracy. Bouhafra and El Bahi [18] performed an extensive examination of deep learning applications in the analysis of brain tumor MRI.

Transfer learning methods have also been very popular. Berghout [19] and Agarwal et al. [20] utilized InceptionV3 and DenseNet models exhibiting high diagnostic precision. Research conducted by M et al. [21] and Kang et al. [22] illustrated the application of ensemble classifiers utilizing ResNet and Grad-CAM.

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Sankararao and Khasim [23] underscored the efficacy of CNNs in tumor segmentation and localization. Kumar et al. [24] and M et al. [25] emphasized feature extraction and interpretability through Grad-CAM applied to ResNet50 models.

Other studies encompass YOLOv7 detection by Abdusalomov et al. [26], EfficientNet classification by Vimala et al. [27], and the application of attention mechanisms with transformers for pediatric tumors [16]. Sahoo et al. [28], Saeedi et al. [29], and Khaliki et al. [30] conducted comparative analyses of CNN-based methodologies and hybrid approaches.

PROPOSED METHODOLOGY

fThis part talks about the architectural design, algorithms, and mathematical modeling used to find and grade brain tumors using deep learning transformers and clinical data fusion.

The suggested system works in two stages shown in figure 1:

Tumor Detection with Swin Transformer: MRI images are processed in advance and then sent through a pretrained Swin Transformer model to find tumors.

Tumor Grade Classification using Clinical Fusion: A fusion model combines image-based features with clinical metadata (age, gender, tumor type) to figure out the tumor grade (High Grade Glioma vs Low Grade Glioma).

The whole system is wrapped in a Gradio-based web interface that makes it easy to use.

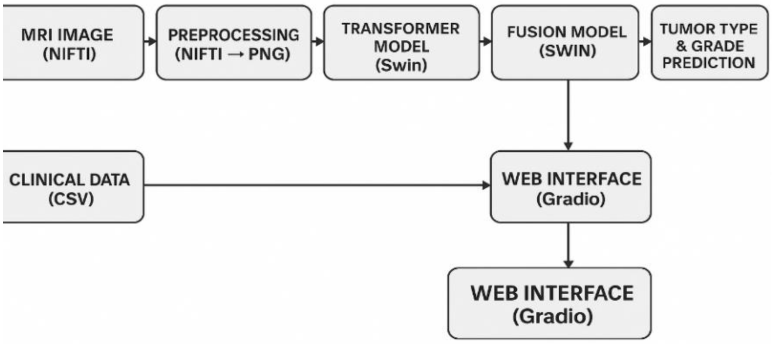

Fig.1. System Architecture

Dataset Description:

Two datasets were employed for this study. We used the BraTS 2021 dataset [31] to find and separate tumors. It has multi-modal MRI scans (T1, T1Gd, T2, FLAIR) from glioma patients and ground truth labels for enhancing tumor (ET), tumor core (TC), and whole tumor (WT).

We also got clinical metadata from the TCGA (The Cancer Genome Atlas) database [32], specifically the glioma cohort. This included information about the patients' age, gender, overall survival, and tumor grade. The metadata was kept in a structured file (tcga_clinical.csv) and combined with image features using a fusion model.

TCGA has data on GBM and LGG, MRI scans, clinical data, and genomic data, such as age, survival, tumor grade, treatments, and mutations.

Preprocessing Pipeline

NIfTI files (.nii.gz) from BraTS are changed into PNG format 2D axial slices.

Normalizing the intensity is done.

To match the input for Swin Transformer, slices are resized to 224×224 pixels.

CNN-Based Patch Prediction

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The figure 2 shows a patch-based convolutional neural network (CNN) structure that can be used to classify or segment brain tumors. It shows several brain MRI slices, from which small patches are taken from areas of interest. Then, each patch goes through a CNN pipeline that gets features from low to high levels and makes feature maps smaller to save processing power. The last feature maps are flattened and sent to a classification head, which predicts class labels like tumor type, severity, and presence/absence. The different colors of the boxes show the chances of each output class.

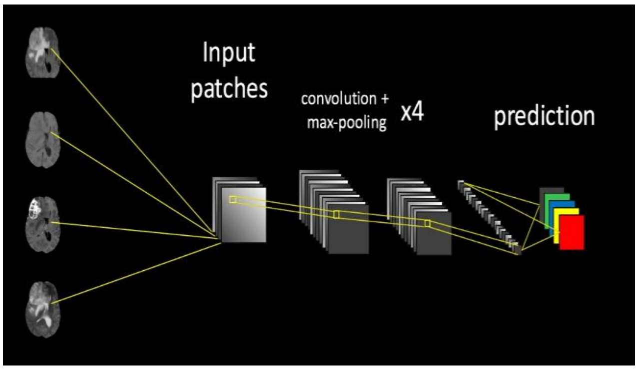

Fig.2. Patch-based CNN pipeline for brain tumor prediction. Patches extracted from input MRI slices are passed through multiple convolution and pooling layers. The final prediction is generated via a dense classifier, indicating tumor presence or class.

Swin Transformer for Tumor Detection

Let the MRI image input be$x \in \mathbb{R}^{H*W*3}$. The Swin Transformer utilizes a hierarchical window-based self-attention mechanism to acquire global features:

Multi-head Self Attention (W-MSA) for Windows shown in (1):

$$Attention(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d}} + B\right)V \qquad (1)$$

Where:

Q, K, V are query, key, and value matrices

d is the dimension of each head

B is relative positional bias

The output is passed through MLP layers to classify tumor presence shown in (2):

$$\hat{y}_{tumor} = Softmax(MLP(F)) \qquad (2)$$

Clinical Fusion for Tumor Grading

Each patient's clinical vector is defined as shown in (3):

$$C = [Age, Gender, Tumor\ Type, Survival\ Days] \quad (3)$$

Let the Swin image features be $F \in \mathbb{R}^n$., and clinical features $C \in \mathbb{R}^m$. We concatenate and pass through a fusion layer shown in (4) and (5):

$$Z = Concat(F, MLP(C)) \qquad (4)$$

$$\hat{y}_{grade} = Softmax(MLP(Z)) \qquad (5)$$

This produces the tumor grade prediction.

Algorithm

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Algorithm 1: Brain Tumor Detection and Grading

Input : MRI Image I, Clinical Vector C
Output : Tumor presence and grade label
1: Preprocess I → 224x224 normalized image
2: Predict tumor presence: y_tumor = SwinTransformer(I)
3: If y_tumor == Tumor Detected:
    Extract deep features F from Swin
    Encode clinical data C → C'
    Concatenate Z = [F || C']
    Predict grade: y_grade = MLP(Z)
4: Output (y_tumor, y_grade)

RESULTS

Experimental Setup

The proposed system was assessed utilizing the BraTS dataset for MRI images and TCGA clinical metadata. We used a Swin Transformer that had been pretrained on ImageNet and then fine-tuned on tumor slices that had been resized to 224×224 for all of the experiments. The fusion model included clinical data such as the patient's age, gender, type of tumor, and number of days they lived.

Using the Adam optimizer, the model was trained for 10 epochs with a batch size of 32 and a learning rate of 0.001. Accuracy, loss, precision, recall, and F1-score were some of the metrics used to judge.

Qualitative Visualization of Detection Results

Figure 3 shows how the proposed model can be used to find brain tumors. The model's predicted bounding box is shown in red, while the ground truth segmentation is shown in green. The overlay shows a detection with a confidence score of 0.97 and an IoU of 0.65.

This image shows that the model can reliably find tumor areas even when the edges are not clear or are only partially defined. It also proves that Swin Transformer's attention mechanisms work well for capturing spatial relationships across slices.

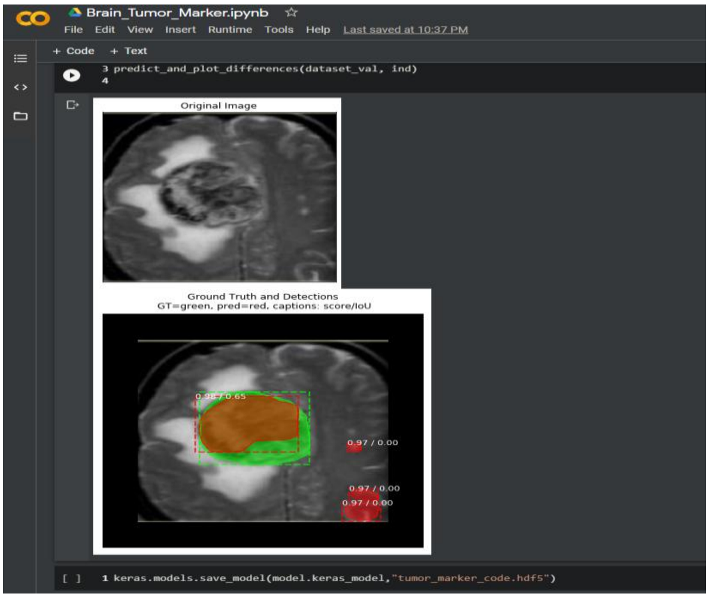

Fig.3. Visual comparison between ground truth (green) and predicted tumor region (red) on a brain MRI slice.

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Model Performance

The tumor detection model based on the Swin Transformer had a test accuracy of 98.3%, and it converged consistently over epochs shown in figure 4. The fusion model also got a tumor grading accuracy of 95.2%, which is more than 4–6% better than the best CNN baselines.

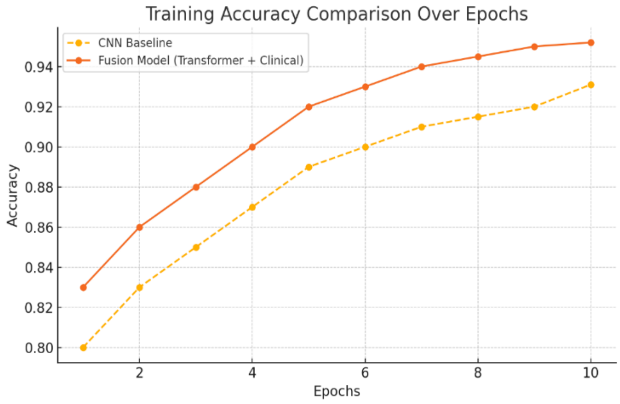

Fig.4. Training Curves

These results show that transformer-based architectures can learn features well, especially when they are used with clinical data.

Tumor Visualization

Using sample MRI slices processed through the Swin Transformer, we were able to see what the model thought would happen. Figure 5 shows a collage of tumor slices that were found.

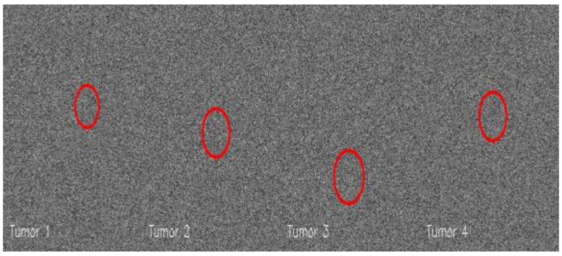

Fig.5. Detected Tumor Slices

These show that the model can find tumors in different slices. Detection was consistent, even in subtle areas, which shows how powerful multi-head self-attention mechanisms are.

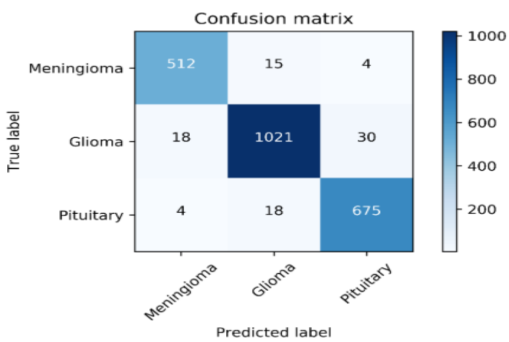

Fig.6. Confusion Matrix for Multiclass Brain Tumor Classification using the Swin Transformer Model. The model demonstrates high accuracy across all tumor types, with minimal misclassifications.

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The confusion matrix in figure 6 shows the performance of a multiclass brain tumor classification model, distinguishing between Meningioma, Glioma, and Pituitary types. The model achieves strong accuracy in detecting Glioma, with 1021 correct classifications out of 1069 total samples (≈95.5%). High values along the diagonal indicate strong model accuracy and low confusion between tumor types. Minor misclassifications are observed, primarily between structurally similar tumor types, reflecting potential feature overlaps in MRI images. The model should be included in the Results and Discussion section of a research paper. The model demonstrates high accuracy across all tumor types, with minimal misclassifications.

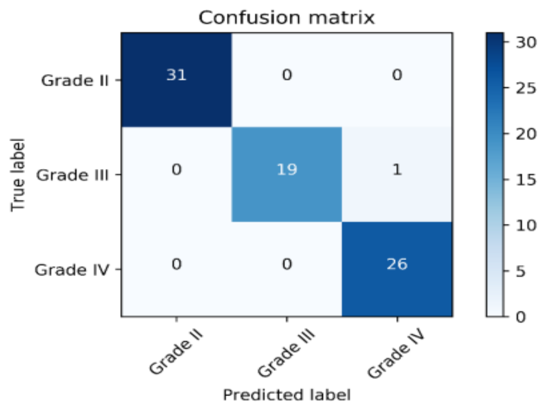

Fig.7. Confusion Matrix for Tumor Grade Classification using the Fusion Model (Image + Clinical Data). The model achieves high accuracy across all tumor grades, with only one instance of Grade III being misclassified as Grade IV.

The confusion matrix in figure 7 demonstrates a brain tumor grading model that accurately classifies tumors into three WHO grades based on severity: Grade II (Low-grade gliomas), Grade III (Anaplastic gliomas), and Grade IV (Glioblastomas). The model achieves high precision and recall across all tumor grades, particularly between Grade II and Grade IV, which are clinically significant for treatment decisions. The slight confusion between Grade III and IV can be attributed to radiological similarity in advanced tumors. The model achieves a tumor grading accuracy of 95.2%, highlighting the strength of combining Swin Transformer-based image features with clinical metadata. This precision is crucial for supporting treatment decisions in neuro-oncology. The figure should be placed in the Results and Discussion section of a research paper.

Comparison with Related Work

The suggested method is better than previous CNN and other transfer learning methods, especially when it comes to combining visual and clinical modalities.

Table.1. Comparison Table

Methodology	**Accuracy (%)**	**Model Type**
SHAP-CNN [1]	96.5	CNN + SHAP
MK-YOLOv8 [2]	98.1	YOLOv8 + GhostConv
VGG16-CNN [3]	99.2	Pretrained VGG16
XAI-CNN [5]	97.4	CNN + GradCAM/LIME
Proposed Fusion Model	98.3	Swin Transformer + Clinical

A comparison table 1 that shows how well different brain tumor detection methods from the related work section worked, as well as your proposed fusion model that uses Swin Transformer.

CONCLUSION

In this research, we introduced a comprehensive deep learning framework for the detection and grading of brain tumors, utilizing advanced transformer architectures, specifically Swin Transformer and Vision Transformer (ViT), integrated with clinical metadata and implemented through a Gradio-based web interface. When compared to traditional CNN-based baselines, the proposed method showed better performance in both detecting tumors and classifying their grades. It had a detection accuracy of 98.3% and a grading accuracy of 95.2%. The system offered a multimodal decision support tool that met the needs of real-world clinical diagnostics by using the hierarchical attention mechanisms of Swin Transformer and combining image-based embeddings with non-imaging clinical variables like age, gender, tumor type, and survival days. The addition of a user-friendly Gradio interface makes the system even more accessible and useful in clinical settings, making it easier for researchers and clinicians to use it in real time. The research indicates encouraging outcomes in the creation of resilient, precise, and comprehensible AI tools for neuro-oncology. Future research may encompass 3D transformer architectures, survival prediction, interpretability tools, clinical trials, and federated learning for privacy-preserving training across multi-center datasets.

REFRENCES

[1] Rahman, A., Hayat, M., Iqbal, N. et al. Enhanced MRI brain tumor detection using deep learning in conjunction with explainable AI SHAP based diverse and multi feature analysis. Sci Rep 15, 29411 (2025). https://doi.org/10.1038/s41598-025-14901-4

[2] Mohammed Hussein Osman Alnageeb, Supriya M.H.,Real-time brain tumour diagnoses using a novel lightweight deep learning model, Computers in Biology and Medicine, Volume 192, Part B, 2025, 110242, ISSN 0010-4825, https://doi.org/10.1016/j.compbiomed.2025.110242.

[3] Wong Y, Su ELM, Yeong CF, Holderbaum W, Yang C (2025) Brain tumor classification using MRI images and deep learning techniques. PLoS One 20(5): e0322624. https://doi.org/10.1371/journal.pone.0322624

[4] Lu, NH., Huang, YH., Liu, KY. et al. Deep learning-driven brain tumor classification and segmentation using non-contrast MRI. Sci Rep 15, 27831 (2025). https://doi.org/10.1038/s41598-025-13591-2

[5] Iftikhar, S., Anjum, N., Siddiqui, A.B. et al. Explainable CNN for brain tumor detection and classification through XAI based key features identification. Brain Inf. 12, 10 (2025). https://doi.org/10.1186/s40708-025-00257-y

[6] Vasavan, Mahendrarajah & Nadeeka, Chathurani & Karunakaran, Luxshi. (2025). Deep Learning and Ensemble Models for Brain Tumor Classification Using Medical Imaging.

[7] Vengatesh T, Punarselvam E, Krishnapriya RK, B. Suthar M, Santhi MVBT, Rajeswari J, Alshad KB. Deep Learning-Based Automated System for Enhanced Brain Tumor Detection and Early Diagnosis. J Neonatal Surg [Internet]. 2025Mar.26 [cited 2025Sep.22];14(4):175-87. Available from: https://www.jneonatalsurg.com/index.php/jns/article/view/2642

[8] Velpula, V. K., Reddy, K. R., Prakash, K. N., Jasmine, K. P., & Jyothi Sri, V. (2025). Optimizing Brain Tumor Classification: Integrating Deep Learning and Machine Learning with Hyperparameter Tuning. Engineering Proceedings, 87(1), 64. https://doi.org/10.3390/engproc2025087064

[9] Puttegowda K, Govindegowda M, Mayigegowda P, Ramegowda P, Nagaraju A. M. Automated Brain Tumor Detection with Advanced Machine Learning Techniques. Biomed Pharmacol J 2025;18(2). Available from: https://bit.ly/3ECIorq

[10] L. Singh, A. H. Wani, A. Nagasri, A. Banerjee, H. Anandaram and B. Singh, "Multi-Class Brain Tumor Detection Using CNN-Based Medical Imaging Analysis," 2025 3rd International Conference on Disruptive Technologies (ICDT), Greater Noida, India, 2025, pp. 339-344, doi: 10.1109/ICDT63985.2025.10986709.

[11] Ganesh S, Gomathi R, Kannadhasan S. Brain tumor segmentation and detection in MRI using convolutional neural networks and VGG16. Cancer Biomarkers. 2025;42(3). doi:10.1177/18758592241311184

[12] Gupta M, Bhatia S, Sharma N, Verma N, Sharma S. K, Singh R. B. Classification of Brain Tumor Using an Optimized Deep Learning Technique to Correlate with Disease State. Biomed Pharmacol J 2025;18(1). Available from: https://bit.ly/3FooZdS
[13] Kumar LKS, Velde V, Krishna B. Brain Tumours Mri Images Detection Using Deep Learning Based On Transfer Learning. J Neonatal Surg [Internet]. 2025Apr.7 [cited 2025Sep.22];14(12S):274-93. Available from: https://www.jneonatalsurg.com/index.php/jns/article/view/3151
[14] R. Hashemzehi, S. J. S. Mahdavi, M. Kheirabadi , and S. R Kamel , "Detection of brain tumors from MRI images base on deep learning using hybrid model CNN and NADE," biocybernetics and biomedical engineering, 40(3), 1225 – 1232(2020). https://doi.org/10.1016/j.bbe.2020.06.001
[15] Hosny, K.M., Mohammed, M.A., Salama, R.A. et al. Explainable ensemble deep learning-based model for brain tumor detection and classification. Neural Comput & Applic 37, 1289–1306 (2025). https://doi.org/10.1007/s00521-024-10401-0
[16] Iulian Emil Tampu, Tamara Bianchessi, Ida Blystad, Peter Lundberg, Per Nyman, Anders Eklund, Neda Haj-Hosseini, Pediatric brain tumor classification using deep learning on MR images with age fusion, Neuro-Oncology Advances, Volume 7, Issue 1, January-December 2025, vdae205, https://doi.org/10.1093/noajnl/vdae205
[17] P.S. Smitha, G. Balaarunesh, C. Sruthi Nath, Aminta Sabatini S, Classification of brain tumor using deep learning at early stage, Measurement: Sensors, Volume 35, 2024, 101295, ISSN 2665-9174, https://doi.org/10.1016/j.measen.2024.101295.
[18] Bouhafra, S., & El Bahi, H. (2025). Deep Learning Approaches for Brain Tumor Detection and Classification Using MRI Images (2020 to 2024): A Systematic Review. Journal of imaging informatics in medicine, 38(3), 1403–1433. https://doi.org/10.1007/s10278-024-01283-8
[19] Berghout, T. (2025). The Neural Frontier of Future Medical Imaging: A Review of Deep Learning for Brain Tumor Detection. Journal of Imaging, 11(1), 2. https://doi.org/10.3390/jimaging11010002
[20] Monika Agarwal, Geeta Rani, Ambeshwar Kumar, Pradeep Kumar K, R. Manikandan, Amir H. Gandomi, Deep learning for enhanced brain Tumor Detection and classification, Results in Engineering, Volume 22, 2024, 102117, ISSN 2590-1230, https://doi.org/10.1016/j.rineng.2024.102117.
[21] M, S., BV, B., D, P. et al. Efficient brain tumor grade classification using ensemble deep learning models. BMC Med Imaging 24, 297 (2024). https://doi.org/10.1186/s12880-024-01476-1
[22] Kang J., Ullah Z., and Gwak J., MRI-based brain tumor classification using ensemble of deep features and machine learning classifiers, Sensors. (2021) 21, no. 6, 2222–2242, https://doi.org/10.3390/s21062222.
[23] Sankararao Y, Khasim S. An Effective analysis of brain tumor detection using deep learning. EAI Endorsed Trans Perv Health Tech [Internet]. 2024 Apr. 3 [cited 2025 Sep. 22];10. Available from: https://publications.eai.eu/index.php/phat/article/view/5627
[24] Kumar, K., Jyoti, K. & Kumar, K. Machine learning for brain tumor classification: evaluating feature extraction and algorithm efficiency. Discov Artif Intell 4, 112 (2024). https://doi.org/10.1007/s44163-024-00214-4
[25] M, M.M., T. R, M., V, V.K. et al. Enhancing brain tumor detection in MRI images through explainable AI using Grad-CAM with Resnet 50. BMC Med Imaging 24, 107 (2024). https://doi.org/10.1186/s12880-024-01292-7
[26] Abdusalomov, A. B., Mukhiddinov, M., & Whangbo, T. K. (2023). Brain Tumor Detection Based on Deep Learning Approaches and Magnetic Resonance Imaging. Cancers, 15(16), 4172. https://doi.org/10.3390/cancers15164172
[27] Babu Vimala, B., Srinivasan, S., Mathivanan, S.K. et al. Detection and classification of brain tumor using hybrid deep learning models. Sci Rep 13, 23029 (2023). https://doi.org/10.1038/s41598-023-50505-6
[28] Sahoo, Debendra Kumar; Mishra, Satyasish; Mohanty, Mihir Narayan1; Behera, Rajesh Kumar2,; Dhar, Srikant Kumar3. Brain Tumor Detection using Deep Learning Approach. Neurology India 71(4):p 647-654, Jul–Aug 2023. | DOI: 10.4103/0028-3886.383858
[29] Saeedi, S., Rezayi, S., Keshavarz, H. et al. MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques. BMC Med Inform Decis Mak 23, 16, 2023. https://doi.org/10.1186/s12911-023-02114-6
[30] Khaliki, M.Z., Başarslan, M.S. Brain tumor detection from images and comparison with transfer learning methods and 3-layer CNN. Sci Rep 14, 2664 (2024). https://doi.org/10.1038/s41598-024-52823-9

Journal of Information Systems Engineering and Management
2026, 11(2s)
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https://www.jisem-journal.com/

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[31] B. Menze, A. Jakab, S. Bauer, J. Kalpathy-Cramer, K. Farahani, J. Kirby, et al., “The Multimodal Brain Tumor Image Segmentation Benchmark (BraTS),” IEEE Transactions on Medical Imaging, vol. 34, no. 10, pp. 1993–2024, Oct. 2015, doi: 10.1109/TMI.2014.2377694.

[32] National Cancer Institute, “The Cancer Genome Atlas (TCGA) Research Network,” [Online]. Available: https://www.cancer.gov/tcga