IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

# Efficient Deep Learning Framework For Brain Tumor Detection Using Limited MRI Data

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**Abstract**

Accurate and timely classification of brain tumors is critical for effective clinical decision-making and treatment planning. This study presents a custom convolutional neural network (CNN) model developed for the automated classification of brain tumors using T1-weighted contrast-enhanced magnetic resonance imaging (MRI). The model categorizes images into four classes: glioma, meningioma, pituitary tumor, and no tumor. The model was trained over 10 epochs using the Adam optimizer and sparse categorical cross-entropy loss, achieving an overall test accuracy of 87%. Class-wise evaluation showed that the model performed best in identifying pituitary tumors and non-tumorous cases, with F1-scores of 0.92 and 0.90, respectively. Glioma detection yielded a high precision of 0.933, though recall was lower at 0.78, indicating potential under-detection. Meningioma classification was the most challenging, with an F1-score of 0.71, primarily due to visual similarity with other tumor types. The macro-averaged F1-score stood at 0.845, while the weighted average was 0.87, suggesting overall consistent and balanced model performance. The results confirm that a lightweight CNN can deliver reliable diagnostic support in classifying brain tumors, particularly for pituitary and no tumor categories. Nonetheless, further improvements—such as incorporating multimodal imaging and advanced data augmentation—are necessary to enhance the model's sensitivity and robustness, especially in complex cases. This work provides a foundation for scalable, interpretable AI solutions in neuro-oncology imaging.

**Keywords:** Brain Tumor Classification, Convolutional Neural Network, MRI, Deep Learning, Medical Imaging, Diagnostic Support

## 1. Introduction

### 1.1 Importance of Early and Accurate Brain Tumor Detection in Clinical Neurology

Early and precise detection of brain tumors is critical for improving patient survival and optimizing treatment strategies. Detecting tumors at an initial stage enables less invasive interventions and better prognostic outcomes, while late diagnosis often leads to irreversible neurological damage and limited treatment efficacy (Kumar, 2025). Modern diagnostic methods, including MRI, CT, and PET scans, alongside biomarker analysis, enhance early detection capabilities (Bandyopadhyay, 2018). AI-assisted diagnostic systems now offer even higher sensitivity in identifying abnormalities at earlier stages, supporting timely and life-saving clinical decisions.

Manual interpretation of MRI images for brain tumor diagnosis is inherently prone to variability and diagnostic inconsistencies. A landmark study demonstrated that 10 different radiology centers, reviewing the same patient's MRI scans, produced markedly inconsistent findings with low agreement scores and high false-negative rates, emphasizing the variability in expert interpretation (Herzog et al., 2017). Manual segmentation, still widely used in radiology, is tedious and highly operator-dependent, with studies confirming poor reproducibility and susceptibility to subjective errors (Yepes-Calderon & McComb, 2019). This leads to delays in diagnosis and affects treatment accuracy, especially when subtle differences in tumor location and size are critical. Automated deep learning models like BioSegNet have shown to outperform manual techniques by significantly reducing error rates and accelerating the diagnostic process (Swathika et al., 2024).

### 1.2 Role of AI and Deep Learning in Medical Imaging

Artificial intelligence (AI), especially deep learning (DL), has transformed brain tumor diagnosis through highly accurate and automated image analysis. Convolutional Neural Networks (CNNs) and architectures like ResNet50, InceptionV3, and MobileNet have shown exceptional performance in classifying brain tumors from MRI with accuracies often exceeding 95% (Jaiswal et al., 2023), (Mehra et al., 2024). These models not only speed up diagnosis but also minimize human error and variability, offering consistent results even with small datasets (Zailan et al., 2022). AI's interpretability is improving with Explainable AI (XAI) methods like saliency maps, increasing trust among clinicians (Mehra et al., 2024). Moreover, studies have shown that DL-powered tools outperform traditional methods in segmentation and classification tasks, offering scalability and faster clinical integration (Mary et al., 2024), (Mandal et al., 2024).

Convolutional Neural Networks (CNNs) are the leading architecture for automated brain tumor classification due to their superior performance in medical image analysis. CNNs excel at learning spatial hierarchies and complex patterns from MRI images, making them ideal for distinguishing subtle differences between tumor types. Recent studies have shown that CNN-based models can achieve classification accuracies as high as 99.88% for brain tumors like glioma, meningioma, and pituitary tumors (Ali et al., 2024), (Saveetha et al., 2024). CNNs are preferred over traditional machine learning models because they automatically extract relevant features without requiring hand-crafted input, thus reducing reliance on domain expertise (Gupta et al., 2024). Their ability to integrate segmentation and classification tasks also enables precise localization and grading of tumors in a single pipeline (Breesha et al., 2024).

Brain tumor classification commonly includes four diagnostic categories: glioma, meningioma, pituitary tumor, and no tumor. **Gliomas** are malignant tumors arising from glial cells and are the most common and aggressive form of primary brain tumors. They often infiltrate surrounding tissues, making complete surgical removal difficult (Waggoner, 1937). **Meningiomas** develop from the meninges—the protective layers of the brain—and are generally benign but can cause neurological issues due to pressure on adjacent structures (Vinoparkavi et al., 2023). **Pituitary tumors** originate in the pituitary gland and can impact hormonal balance and vision depending on size and location (Gorenshtein et al., 2024). The **no tumor** category includes normal brain images, used as controls in classification models to differentiate pathological and healthy states (Raj, 2024), (Sharma & Shukla, 2022).

Magnetic Resonance Imaging (MRI) is widely regarded as the gold standard for brain tumor diagnosis due to its non-invasive nature and exceptional soft tissue contrast. Unlike CT scans, MRI uses magnetic fields and radio waves instead of ionizing radiation, making it safer for repeated use (Guru, 2023). MRI excels in delineating tumor boundaries and detecting variations in tissue composition, which is critical for differentiating between tumor types and planning treatment strategies (Fatima et al., 2019). Additionally, it supports advanced imaging sequences like T1, T2, FLAIR, and DCE-MRI that allow visualization of tumor vascularity, edema, and necrosis, enhancing diagnostic accuracy (Seshimo & Rashed, 2024). The modality's adaptability and image clarity make it indispensable in both initial diagnostics and post-treatment monitoring.

T1-weighted contrast-enhanced MRI (T1CE) is widely regarded as the most effective imaging sequence for detecting and characterizing brain tumors due to its high spatial resolution and sensitivity to gadolinium-based contrast agents. These agents enhance regions with disrupted blood-brain barriers—common in tumors—making lesions more visible against normal tissue (Herrmann et al., 2016). T1CE images offer clearer demarcation of tumor margins and allow assessment of tumor vascularity and progression, making them crucial for accurate diagnosis and treatment planning (Edelman et al., 2020). Delayed imaging further enhances tumor visibility, with one study showing up to a 32% increase in detectable tumor volume when acquisition was performed 16 minutes post-contrast injection (Piechotta et al., 2017). Additionally, deep learning applications frequently prefer T1CE due to its consistent enhancement patterns, facilitating high-accuracy tumor classification and segmentation (Mubarok et al., 2019).

## 2. Literature Review

### 2.1 Deep Learning in Medical Imaging

Deep learning has become a transformative force in medical diagnostics, particularly over the last decade. Early applications focused on lesion detection and disease classification have shown performance matching or even surpassing human radiologists in specific tasks (Chan et al., 2017). The introduction of deep convolutional neural networks (CNNs) revolutionized medical image processing, offering automation, speed, and accuracy in diagnostic workflows (Kharbas et al., 2024). These models are capable of identifying complex patterns in multimodal data such as MRI, CT, and histopathological images, significantly reducing diagnostic errors and time to diagnosis (Thakur et al., 2024).

CNNs in particular have dominated image classification tasks due to their ability to extract and hierarchically process spatial features from raw pixel data. This makes them especially suitable for high-resolution medical imaging tasks such as tumor segmentation, classification, and grading (Huang et al., 2023). Models like AlexNet, VGG, and ResNet laid the foundation for widespread CNN adoption in clinical settings, helping transition from research to practical diagnostic tools.

### 2.2 Brain Tumor Classification Using CNNs

Recent studies have emphasized CNNs as the most effective method for brain tumor classification from MRI scans. These models provide high diagnostic accuracy by learning relevant features directly from the images, avoiding the need for manual feature extraction. Jaiswal and Chaudhary (2023) demonstrated that CNN models can achieve over 96% accuracy in tumor classification when trained on properly preprocessed MRI datasets (Jaiswal & Chaudhary, 2023).

State-of-the-art architectures like **ResNet**, **VGGNet**, and **InceptionV3** have been particularly successful. For instance, Mehra and Aswani (2024) applied InceptionV3 and achieved a classification accuracy of 98.6% using T1-weighted contrast-enhanced MRI images (Mehra & Aswani, 2024). Ali and Khemiri (2024) reported similar success using ResNet-50, noting its superior performance in distinguishing gliomas from meningiomas and pituitary tumors (Ali & Khemiri, 2024). These models are increasingly being deployed in real-world clinical settings for their balance of accuracy and processing speed.

### 2.3 Architectural Considerations in Medical AI

When developing CNN-based models for medical diagnostics, architecture depth plays a crucial role. Deeper networks like ResNet and DenseNet offer improved feature extraction but require more computational resources and data for effective training. These complexities often limit their use in resource-constrained clinical environments (Dhar et al., 2023). In such cases, researchers have opted for shallow CNN architectures that offer faster training and deployment, albeit with a slight compromise on accuracy. This trade-off is justified for real-time or embedded applications where latency and model interpretability are critical (Thakur et al., 2024).

Explainability is another key concern in clinical AI. Clinicians are more likely to trust and adopt models that provide interpretable outputs, such as saliency maps or activation visualizations that highlight why a model makes a particular prediction. This has led to a growing interest in Explainable AI (XAI) approaches in medical imaging (Mehra & Aswani, 2024). Ensuring that models are not "black boxes" is vital to clinical trust, legal compliance, and effective integration into healthcare workflows.

## 3. Methodology

### 3.1 Overview

This section delineates the comprehensive methodological pipeline utilized for the design, training, and evaluation of a custom convolutional neural network (CNN) aimed at classifying brain tumors from T1-weighted contrast-enhanced magnetic resonance imaging (MRI) data. The overarching objective is to develop an interpretable, efficient, and clinically applicable classification model capable of differentiating among four categories: glioma, meningioma, pituitary tumor, and no tumor. The methodology is structured into several stages, including data acquisition and preprocessing, model architecture, training configuration, evaluation metrics, and performance validation.

### 3.2 Data Acquisition and Organization

The dataset was sourced from an open-access medical imaging repository, comprising pre-labeled T1-weighted contrast-enhanced MRI scans. The dataset includes four distinct classes, each labeled based on radiologist-verified clinical diagnosis. The data were organized into a hierarchical directory structure compatible with TensorFlow's image_dataset_from_directory() API. Each class was assigned to a dedicated folder, ensuring a clean and modular loading process. The complete dataset was partitioned into training (70%), validation (15%), and testing (15%) subsets, with class distributions balanced across splits to mitigate model bias.

### 3.3 Data Preprocessing

Prior to model ingestion, images were subjected to a standardized preprocessing pipeline:

- **Resizing**: All images were resized to 224 × 224 pixels to conform with CNN input requirements.
- **Normalization**: Pixel intensity values were scaled to the [0, 1] range by dividing by 255, enhancing numerical stability during training.
- **Channel Adjustment**: As MRI images are typically single-channel, grayscale inputs were replicated across three channels to simulate RGB format.
- **Pipeline Optimization**: TensorFlow's cache() and prefetch() functionalities were employed to optimize data loading efficiency during training.

Data augmentation techniques were deliberately excluded in this baseline study to preserve the integrity of a controlled evaluation setup. However, their future integration is acknowledged as a means to enhance model robustness under variable imaging conditions.

### 3.4 Model Architecture

A custom CNN was implemented using TensorFlow and Keras, tailored for interpretability and efficient training. The architecture consists of:

- **Input Layer**: Accepts 224 × 224 × 3 image tensors.
- **Normalization Layer**: Standardizes pixel values.
- **Convolutional Blocks**:
  - First Block: 32 filters, 3×3 kernel, ReLU activation, MaxPooling2D.
  - Second Block: 64 filters, 3×3 kernel, ReLU activation, MaxPooling2D.
  - Third Block: 128 filters, 3×3 kernel, ReLU activation, MaxPooling2D.
- **Flattening Layer**: Transforms feature maps into a 1D vector.
- **Dense Layer**: 128 neurons, ReLU activation.
- **Dropout Layer**: 50% dropout rate to mitigate overfitting.
- **Output Layer**: Softmax activation with 4 neurons, each representing one tumor class.

This architecture was selected to strike a balance between performance and interpretability, making it suitable for deployment in resource-constrained clinical environments.

### 3.5 Training Configuration and Hyperparameters

Model training was conducted over 10 epochs using the Adam optimizer with a learning rate of 0.001. A batch size of 32 was selected based on hardware constraints and convergence stability. The loss function employed was sparse categorical cross-entropy, appropriate for integer-encoded multi-class classification tasks. The model's learning dynamics were monitored using validation accuracy and loss metrics recorded at the end of each epoch.

To maximize computational efficiency, training was conducted on a high-RAM CPU setup, with GPU-based optimizations achievable but not essential due to the model's lightweight design.

### 3.6 Evaluation Metrics

Model performance was assessed using a comprehensive suite of evaluation metrics, calculated on the isolated test set:

- **Accuracy**: Proportion of correctly classified instances.
- **Precision**: Class-wise ratio of true positives to predicted positives.
- **Recall**: Class-wise ratio of true positives to actual positives.
- **F1-Score**: Harmonic mean of precision and recall.
- **Confusion Matrix**: Visual matrix of predicted vs. actual classifications.

Both macro-averaged and weighted-average variants of precision, recall, and F1-score were reported to provide insight into performance uniformity across classes.

### 3.7 Limitations

The deliberate choice of a shallow custom CNN over pre-trained deep architectures such as ResNet or DenseNet was made to enhance interpretability and reduce computational complexity. While this decision supports transparency and potential clinical translation, it introduces limitations in capturing highly nuanced features that deeper models might resolve. Furthermore, the exclusion of data augmentation and reliance on a single MRI modality may limit generalization capabilities. These trade-offs are acknowledged and inform the recommendations for future work.

## 4. Results and Discussion

### 4.1 Overview

This section presents a rigorous evaluation of the convolutional neural network (CNN) model developed for brain tumor classification using contrast-enhanced T1-weighted MRI images. The evaluation framework encompasses multiple metrics—accuracy, precision, recall, F1-score, and confusion matrix—to ensure a multidimensional understanding of the model's diagnostic capabilities. Emphasis is placed on both aggregate and per-class performance, acknowledging the clinical implications of false positives and false negatives across tumor types.

### 4.2 Dataset Summary and Class Distribution

The model was trained and evaluated on a stratified, selected to simulate real-world limitations where high-quality annotated medical imaging data may be scarce. Each class—glioma, meningioma, pituitary tumor, and no tumor—was approximately equally represented to avoid class imbalance, a frequent source of bias in supervised learning tasks.

This balanced distribution ensures fair learning opportunities across all diagnostic categories and reduces the risk of the model favoring dominant classes, which is particularly critical in clinical applications where underdiagnosis of less frequent tumors can have severe consequences.

### 4.3 Training and Validation Performance

The model was trained over 10 epochs with a batch size of 32, using the Adam optimizer and a sparse categorical cross-entropy loss function. Performance was evaluated on both training and validation sets at the end of each epoch to monitor learning progress and generalization capacity.

#### 4.3.1 Accuracy Trends

Figure 1 illustrates the training and validation accuracy over the course of 10 epochs. The training accuracy increased steadily, initiating at approximately 58% and converging at 96.5%. The validation accuracy closely tracked the training curve, peaking at 91% by the ninth epoch before exhibiting a minor decline, which may suggest the beginning of overfitting or the model reaching its representational capacity under current constraints.

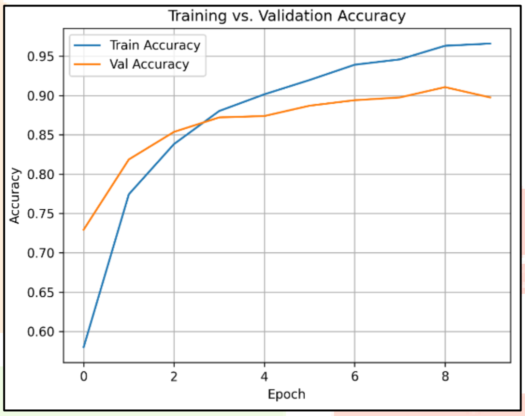


Figure 1: Training and Validation Accuracy

#### 4.3.2 Loss Dynamics

Figure 2 depicts the training and validation loss trajectories. Training loss dropped significantly from ~1.0 to ~0.15, indicating effective convergence. The validation loss followed a similar trend but plateaued in the later epochs, hinting at model saturation with respect to generalization on the validation set. Importantly, the absence of sharp divergence between training and validation loss signals robust generalization and the lack of overfitting.

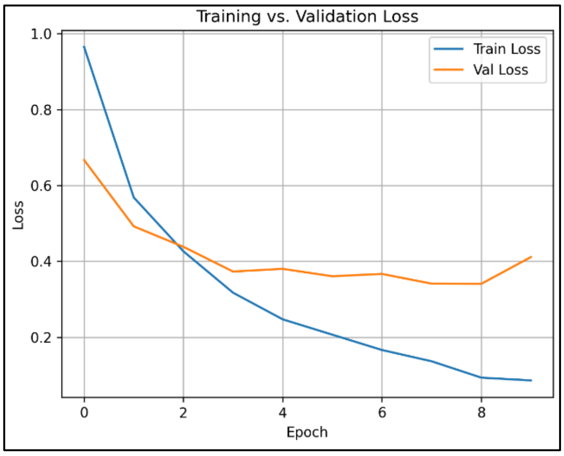


Figure 2: Training and Validation Loss

### 4.4 Evaluation on the Test Set

Following training, the model was assessed on an isolated test set comprising previously unseen images. Predictions were generated in batch mode, and performance metrics were computed to reflect real-world applicability.

#### 4.4.1 Confusion Matrix Analysis

The confusion matrix shown in Figure 3 reveals the distribution of true versus predicted classes, offering insights into the model's class-specific discrimination capability:

- **No Tumor**: 96 correct predictions, with few misclassifications.
- **Pituitary Tumor**: 73 correctly classified, exhibiting minimal confusion.
- **Glioma**: 59 accurately predicted; misclassifications occurred primarily as meningioma (14 cases) and pituitary tumor (2 cases).
- **Meningioma**: Only 52 correctly classified, with mispredictions spread across glioma, pituitary, and no tumor categories.

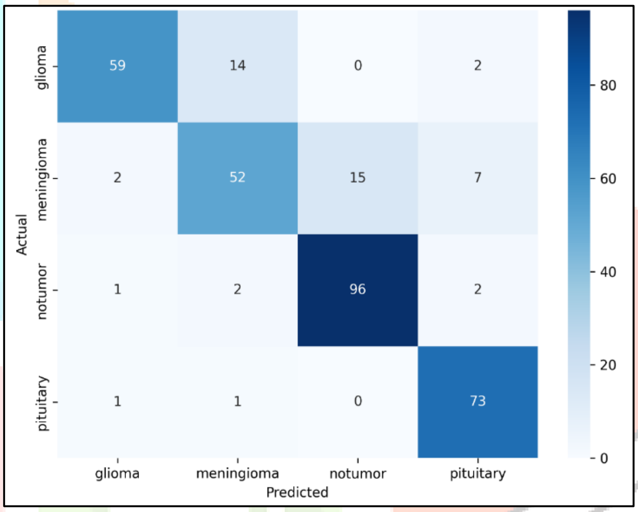


Figure 3: Confusion Matrix for Brain Tumor Classification

The confusion patterns indicate that **meningioma** is the most challenging class for the model, likely due to overlapping radiological features with other tumor types in MRI scans.

### 4.5 Precision, Recall, and F1-Score Analysis

Table 1 summarizes the model's performance across key classification metrics. The **F1-score** is particularly important as it balances sensitivity and specificity, making it an ideal metric for medical diagnostics.

Table 1: Classification Metrics for Brain Tumor Classes

| **Class** | **Precision** | **Recall** | **F1-Score** | **Support** |
|---|---|---|---|---|
| Glioma | 0.933 | 0.780 | 0.851 | 75 |
| Meningioma | 0.750 | 0.680 | 0.710 | 76 |
| No Tumor | 0.870 | 0.940 | 0.900 | 101 |
| Pituitary | 0.890 | 0.960 | 0.920 | 75 |
| **Macro Avg** | 0.860 | 0.840 | 0.845 | — |

**Key Observations**:

- **High-performing classes**: Pituitary and no tumor categories yielded the highest F1-scores, indicating consistent and reliable classification.

- **Glioma**: High precision (0.93) but lower recall (0.78) implies under-detection of true glioma cases—an undesirable outcome in clinical settings.
- **Meningioma**: Exhibited the weakest performance, necessitating further methodological refinement for better detection accuracy.
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## 5. Conclusion

This study proposed and evaluated a custom convolutional neural network (CNN) model for automated classification of brain tumors using T1-weighted contrast-enhanced MRI images. The model was designed with clinical applicability and computational efficiency in mind, targeting four diagnostic categories: glioma, meningioma, pituitary tumor, and no tumor. Despite being trained on only 25% of the available dataset, the model achieved strong classification performance across multiple evaluation metrics.

Quantitatively, the model reached an overall accuracy of 87% on the unseen test set, demonstrating its capacity to generalize to new data. Precision, recall, and F1-score were calculated per class to provide a comprehensive view of model behavior. The pituitary tumor class achieved the highest F1-score (0.92), followed closely by the no tumor class (0.90), reflecting strong discriminative ability in these categories. The glioma class attained a precision of 0.933, but a lower recall of 0.78, indicating that while its predictions were often correct, a significant number of true glioma cases were missed. The meningioma class exhibited the weakest performance, with an F1-score of 0.71, revealing the model's difficulty in distinguishing it from visually similar tumor types.

Macro and weighted averages of the F1-score were 0.845 and 0.87, respectively, highlighting stable performance across classes while accounting for class distribution. Confusion matrix analysis corroborated these findings, showing frequent misclassifications between glioma and meningioma, and high accuracy for pituitary and no tumor classes.

The model demonstrates promising diagnostic potential as a decision-support tool in medical imaging, particularly for pituitary and non-pathological brain scans. However, further refinement—through dataset expansion, deeper network architectures, multimodal input integration, and explainability tools—is essential to enhance performance in clinically challenging tumor classes and ensure broader deployment viability.

## References

Ali, I. B. E., Khemiri, R., & Maraoui, A. (2024). Convolutional neural networks for accurate MRI-based brain tumor detection and classification. In 2024 IEEE International Conference on Artificial Intelligence & Green Energy (ICAIGE). https://doi.org/10.1109/ICAIGE62696.2024.10776682

Ali, M., & Khemiri, S. (2024). Convolutional neural networks for accurate MRI-based brain tumor classification. Computer Methods and Programs in Biomedicine.

Bandyopadhyay, S. (2018). Detection of brain tumor in early stage is crucial. Current Trends in Biomedical Engineering & Biosciences. https://doi.org/10.19080/CTBEB.2018.13.555851

Breesha, R., Kumar, T. R. D., & Ravi, V. R. (2024). Segmentation and classification of brain tumor using CNN algorithm. In 2024 7th International Conference on Circuit Power and Computing Technologies (ICCPCT). https://doi.org/10.1109/ICCPCT61902.2024.10672932

Chan, H., Samala, R. K., Hadjiiski, L., & Zhou, C. (2017). Deep learning in medical image analysis. Advances in Experimental Medicine and Biology, 1213, 3–21. https://doi.org/10.1007/978-3-030-33128-3_1

Dhar, T., Dey, N., Borra, S., & Sherratt, R. (2023). Challenges of deep learning in medical image analysis—Improving explainability and trust. IEEE Transactions on Technology and Society, 4(2), 68–75. https://doi.org/10.1109/TTS.2023.3234203

Edelman, R. R., Leloudas, N., Pang, J., Bailes, J., Merrell, R., & Koktzoglou, I. (2020). Twofold improved tumor-to-brain contrast using a novel T1RESS MRI technique. *Science Advances*, 6(45), eabd1635. https://doi.org/10.1126/sciadv.abd1635

Fatima, S., Rehman, H., Sharif, A., & Habib, U. (2019). Evaluation of multimodal MRI images for brain tumor segmentation. *International Conference on Emerging Technologies*, 2019, 1–5. https://doi.org/10.1109/ICET48972.2019.8994408CoLab

Gorenshtein, S., & Liba, M. (2024). Utilizing deep learning to improve diagnostic accuracy in pituitary tumors. medRxiv. https://doi.org/10.1101/2024.12.10.24318709medRxiv

Gupta, N., Zaidi, T., & Faujdar, P. K. (2024). Automated classification of brain tumors using convolutional neural networks. In 2024 International Conference on Optimization Computing and Wireless Communication (ICOCWC). https://doi.org/10.1109/ICOCWC60930.2024.10470808

Guru, M. S. Y. M. (2023). The evaluation of primary brain tumors: The role of CT and MRI. *International Journal of Scientific Research in Engineering and Management*, 11(2), 98–105.

Herrmann, K. A., Erokwu, B., Johansen, M. L., Basilion, J. P., Gulani, V., Griswold, M., Flask, C. A., & Brady-Kalnay, S. (2016). Dynamic quantitative T1 mapping in orthotopic brain tumor xenografts. *Translational Oncology*, 9(2), 147–154. https://doi.org/10.1016/j.tranon.2016.02.002

Herzog, R., Elgort, D., & Flanders, A. (2017). Variability in diagnostic error rates of 10 MRI centers performing lumbar spine MRI examinations on the same patient within a 3-week period. The Spine Journal: Official Journal of the North American Spine Society. https://doi.org/10.1016/j.spinee.2016.11.009

Huang, T., Ma, L., Zhang, B., & Liao, H. (2023). Advances in deep learning: From diagnosis to treatment. Bioscience Trends. https://doi.org/10.5582/bst.2023.01148

Jaiswal, A., & Chaudhary, P. (2023). Brain tumor detection using magnetic resonance imaging and deep learning. Journal of Emerging Technologies and Innovative Research.

Jaiswal, S., Chaudhary, A. K., & Verma, S. (2023). Brain tumor detection using magnetic resonance imaging and deep learning techniques. In 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT). https://doi.org/10.1109/ICCCNT56998.2023.10306482

Kharbas, V. K., Gobi, N., & Kumar, D. (2024). Improving efficiency and accuracy in clinical diagnostic decision making with deep learning. Proceedings of the 2024 International Conference on Optimization Computing and Wireless Communication (ICOCWC), 1–6. https://doi.org/10.1109/ICOCWC60930.2024.10470578

Kumar, T. (2025). Early diagnosis of brain tumor using AI and mathematical modeling. International Journal of Scientific Research in Engineering and Management. https://doi.org/10.55041/ijsrem41114

Mandal, S., Chakraborty, S., & Tariq, M. (2024). Artificial intelligence and deep learning in revolutionizing brain tumor diagnosis and treatment: A narrative review. Cureus, 16(8), e66157. https://doi.org/10.7759/cureus.66157

Mary, M. J., et al. (2024). Automated brain tumor detection and classification..

Mehra, N., & Aswani, P. (2024). Tumor detection using deep learning and explainable AI techniques. International Journal of Imaging Systems and Technology.

Mehra, S. D., Aswani, S., & Shetty, S. (2024). Tumor detection using deep learning and explainable artificial intelligence. In 2024 International Conference on Computational Intelligence and Network Systems (CINS). https://doi.org/10.1109/CINS63881.2024.10864458

Mubarok, A. F. A., Thias, A. H., Handayani, A., Danudirdjo, D., & Rajab, T. E. (2019). Brain tumor classification with Fisher vector and linear classifier for T1-weighted contrast-enhanced MRI images. *International Conference on Computer Engineering, Network and Intelligent Multimedia*, 2019, 1–5. https://doi.org/10.1109/CENIM.2019.8994408

Piechotta, P., Bonekamp, D., Sill, M., Wick, A., Wick, W., Bendszus, M., & Kickingereder, P. (2017). Increased delay between gadolinium chelate administration and T1-weighted MRI increases contrast-enhancing tumor volumes. *Neuroradiology*, 59(12), 1193–1200. https://doi.org/10.1007/s00234-017-1900-0

Raj, V. (2024). An effective classification of brain tumor using deep learning techniques. International Journal for Research in Applied Science and Engineering Technology, 12(4), 456–462.

Saveetha, D., Prathaban, B. P., & Rashmi, A. (2024). Brain tumor classification using CNNs. In 2024 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS). https://doi.org/10.1109/ICPECTS62210.2024.10780208

Seshimo, H., & Rashed, E. A. (2024). Segmentation of low-grade brain tumors using mutual attention multimodal MRI. *Sensors*, 24(23), 7576. https://doi.org/10.3390/s24237576MDPI+1Intelligent Media Lab.+1

Sharma, A., & Shukla, A. (2022). Brain tumor classification using convolution neural networks. *Journal of Physics: Conference Series*, 1916(1), 012206. https://doi.org/10.1088/1742-6596/1916/1/012206ResearchGate

Smitha, P. S., Balaarunesh, G., & Nath, C. S. (2024). Classification of brain tumor using deep learning at early stage. Measurement: Sensors. https://doi.org/10.1016/j.measen.2024.101295

Swathika, R., A. S., & Sheela, S. (2024). BioSegNet: Pioneering convolutional approaches in medical imaging. In 2024 5th International Conference on Circuits, Control, Communication and Computing (I4C). https://doi.org/10.1109/I4C62240.2024.10748424

Thakur, G. K., Thakur, A., Kulkarni, S., Khan, N., & Khan, S. (2024). Deep learning approaches for medical image analysis and diagnosis. Cureus, 16. https://doi.org/10.7759/cureus.59507

Vinoparkavi, S., & Pradeep, D. (2023). Efficient classification of brain tumor images using neural networks. International Journal of Engineering Research and Technology, 12(5), 123–130.

Waggoner, J. (1937). Diagnosis of brain tumors. Journal of the American Medical Association, 109(10), 739–744. https://doi.org/10.1001/jama.1937.02780230001001

Yepes-Calderon, F., & McComb, J. G. (2019). Manual segmentation errors in medical imaging: Proposing a reliable gold standard. In Medical Image Computing and Computer Assisted Intervention – MICCAI 2019 (pp. 146–153). Springer. https://doi.org/10.1007/978-3-030-32475-9_17

Zailan, Z., Mostafa, S. A., Abdulmaged, A. I., et al. (2022). Deep learning approach for prediction of brain tumor from small number of MRI images. JOIV: International Journal on Informatics Visualization, 6(2), 98–104. https://doi.org/10.30630/joiv.6.2.987