Hybrid Deep Learning for Brain Tumor Segmentation in MRI Videos

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Abstract: Precise Brain Tumor Detection from MRI video scans is essential for effective treatment planning and diagnosis at early stage. Current methods often fight to model spatio-temporal dependencies, address class imbalance, and generalize across heterogeneous datasets. To overcome these limitations, this paper proposes deep learning framework for automated brain tumor segmentation in MRI video sequences. The proposed module employs a ResNet3D–LSTM architecture to extract discriminative spatio-temporal features, where ResNet3D acquires volumetric spatial information and LSTM develops temporal continuity across sequential MRI frames. For accurate tumor segmentation, a hybrid UNet–Feature Pyramid Network is applied to facilitate successful multi-scale feature fusion, capturing both local structural details and global contextual information. Experimental evaluations prove superior performance, with classification accuracies of 95% and 97% and Dice similarity coefficients ranging from 0.89 to 0.93 across multiple datasets. The proposed work confirms a strong and effective solution for MRI video-based brain tumor analysis, increasing diagnostic accuracy, generalization capability, and clinical applicability.

Keywords: Brain Tumor Detection, Spatio-Temporal Features, 3D CNN - LSTM, Attention Mechanism.

1 Introduction

Brain tumors are one of the extremely dangerous neurological conditions, producing substantial challenges for precise diagnosis and treatment projection. Magnetic resonance imaging (MRI) is the preferred non-invasive modality for the rapid advancement of deep learning has significantly transformed medical image analysis by enabling automatic learning of hierarchical and discriminative feature representations. Convolutional neural networks (CNNs) have proven amazing performance in brain tumor classification and segmentation tasks. However, most existing deep learning frameworks run on static MRI slices and decline to exploit the temporal dependencies inherent in MRI video or sequential scan data. As a result, these methods are frequently insensitive to minute spatiotemporal changes that are essential for precise tumor characterization and progression research. Recent research has

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investigated hybrid architectures that combines CNNs with recurrent neural networks (RNNs), including long short-term memory (LSTM) networks, for modeling temporal information to overcome this problem. Regardless of these initiatives, the functional adoption of manycurrent models are hampered by their enormous computational complexity, bounded interpretability, and are unsuccessful in fully utilizing the benefits of spatial and temporal feature learning. The restricted use of key-frame selection algorithms that can exhibit analysis on diagnostically appropriate frames is another essential investigation restraint. Lacking subsequent working gains, managing every frame in an MRI sequence repeatedly lead to doubled calculations and reduced efficiency. Frameworks established using data from an exact imaging procedure recurrently indicate reduced performance when verified on datasets composed of different scanners, patient populations, or achievement settings, indicating that inadequate cross-domain generalization relics a key challenge. The proposed research shows a hybrid deep learning model which incorporates domain variation methods, attention mechanisms, and modern spatiotemporal modeling to passage these gaps [4]– [6]. The advised method figures out strong spatial and temporal characteristics from MRI video sequences by enhancing LSTM networks with the ResNet3D framework. To influence clinically proper frames, an attention-based key frame selection technique is proposed, which increases model interpretability and computational effectiveness. UNet model and Feature Pyramid Networks (FPN) are used to advance precise boundary description and efficient multi-scale feature fusion for tumor segmenting.

However, for commanding temporal coherence and resolving class imbalance, a hybrid loss function that combines Dice loss, and temporal dependability limits is proposed. The summarized approach gets contemporary performance in segmentation precision, tumor class, and generalization round a range of datasets, matching to vast experimental results.

2 Motivation and Contributions

The spatiotemporal complexity of MRI video data originates from substantial problems for present methods, even if Magnetic Resonance Imaging (MRI) gives specific structural and temporal perception. While many video-based methods may not be able to sphere the spatial features that are required for specific segmentation, the advancement of tumor characteristics is not attained by static image-based frameworks. Scientific usefulness of founded systems is severely problematic by their incapable generalization across heterogeneous datasets, high calculating overhead, and inadequate interpretability.

These limitations shove the growth of a fusion model that agreements with interpretability and precision simultaneously.

The significant role of the work is listed below:

- ResNet3D–LSTM model is proposed to effectively format spatial arrangements and temporal dynamic contrast in MRI video sequences
- A Transformer-based attention process is combined to acknowledge and organize diagnostically appropriate frames.
- A unified Feature Pyramid Network (FPN) UNet model is used to attain specific tumor edge outlining.
- A hybrid loss function is premeditated to address class unevenness.
- Cross-Domain Generalization to advance sturdiness and generalization performance.

Jointly, the listed roles support a complete and clinically useful model that increases the high-performance models for brain tumor detection and segmentation.

3 Review of Existing Models

Over recent years, developments have been made in brain tumor detection, categorization, and segmentation by using machine learning and deep learning techniques. Current research focusses extensive evolution in algorithm strategy, combining learning tactics, transferring learning procedures, and the making of datasets. Together, a wide indication is extended by these efforts of the current state of the field, underlining both the effective advantages and current meetings. Previous investigations concentrating on traditional machine learning (ML) methods combined with manually designed feature extraction procedures. Kumar and others [1] estimated various ML classifiers for brain tumor classification and recognized that the overall implementation is meaningly influenced by the superiority and biased power of the pulled-out features. Depending on this research line, Das and Goswami [2] analyzed hybrid algorithms and transferred learning approaches, revealing intensified accuracy in classification and segmentation of MRI data. In collection to image-based analysis, Abdelrahman Ali et al. [3] proposed a ML-advanced surface plasmon resonance biosensor, giving the capability of non- imaging methods as additional tools for each cancer detection. To reinforce research initiated on Deep Learning (DL), Verma et al. [4] proposed the JMCD dataset, acknowledging for organized inference of cutting-edge neural network structures. Liu et al. [5] proposed that blending CNN-based feature extraction with conventional classifiers remarkably increases the precision of tumor categorization in MRI scans. In a similar way, Mathivanan et al. [6] directed pre-trained DL frameworks to enhance detection exactness, focusing the utilities of transfer learning when trading with scarce amounts of described medical data. Conventional ML methodologies are however used in tumor categorization. Huang and Dai [7] modeled estimating paradigms using conventional ML means, focusing on the inference of feature standardization and data preprocessing. Singh and Lobiyal [8] incorporated a relative investigation of long-established ML representations and deep transfer learning procedures, uncovering that deep frameworks are more appropriate for handling giant datasets and elaborate feature

representations. To face broad view trials, Biradar and Virupakshappa [9] described a multi- source transfer learning model that enriched robustness when handling with diverse imaging datasets. Keeping segmentation, Mansur et al. [10] had given a region-aware DL framework, giving perceptions into network designs openly pointed at genuine tumor edge categorization. Pandey and Bhandari [11] projected a morphological transfer learning technique assembled on YOLOv5, which set a standard for instantaneous tumor detection. Admitting the suggestion of clinical trust, Hosny et al. [12] projected an explainable collaborative DL model that can explain categorization conclusions.

In an analogous method, AlShowarah [13] exhibited us Deep Cancer, an end-to-end system that unites DL for the automatic detection and analysis of tumors. Additionally, Nayak et al. [14] showed how ML techniques can be employed to both detection and segmentation tasks, connecting two necessary parts of medical image analysis. M et al. [15] suggested categorization methodologies depending on collaborative DL to honestly grade brain tumors, assuming one of the most complex analytical conflicts. Even though these methods have yielded heartening outcomes, several challenges still occur, such as insufficient modeling of spatio-temporal associations, substantial computational demands, imperfect clarity, and fragile performance when applied across different fields. These encounters drive the formation of a unified hybrid framework that magnificently associates spatio-temporal learning, attention mechanisms, dependable segmentation, and domain adaptation, as introduced in the study. Finally, Khaliki and Başarslan [16] have presented a systematic comparison between transfer learning and the more traditional CNN architectures to prove deeper architectures are effective for image analysis.

4 Proposed Design

In this segment, the architecture and functioning design of an iterative hybrid DL framework developed for precise brain tumor detection and segmentation from MRI video sequences is presented. The recommended framework aims to confront major inadequacies of current approaches, such as extreme computational complexities and lower processing effectiveness. As shown in Fig. 1., the framework is additionally expanded beyond detection and segmentation to comprise post-treatment prognostic estimation and calculation of tumor recurrence using progressive MRI data. The suggested approach drives the spatio-temporal features of MRI video sequences that sorts how tumors increase over time, this is needed for calculating treatment usefulness and prognostication imaginable recurrence. Numerous complicated factors are united in the model that are statistically outlined and scientifically acquainted for analytical investigation. Initially, MRI video sequence input undergoes through a preprocessing stage to achieve spatial location and uphold temporal composure between frames. The T here notifies the total number of frames in the order, The H and W variables show the spatial outcome, and so the C represents the

amount of image channels. After preprocessing, spatio-temporal feature extraction is achieved by means of a hybrid 3D CNN–LSTM algorithm to effectively secure both structural verification and temporal evolution of tumor growths. Spatial feature representations are dragged using a ResNet3D backbone, which supports deep hierarchical feature learning while explaining rare gradient issues. The spatial feature abstraction method is mathematically communicated in (1).

$$Fs = fResNet3D(X), Fs \in R'(T \times ds) \quad (1)$$

Where, fResNet3D obtains frame-wise spatial interpretations, and ds is the spatial feature dimensionality in the practice. The temporal relationships between frames, which are crucial to understanding tumor evolution, are modeled using LSTM via equation (2)

$$Ft = fLSTM(Fs), Ft \in R'(T \times dt) \quad (2)$$

Where, dt is the temporal feature dimensionality sets. The representation Ft provides a basis for further downstream tasks.
Attention-based key frame detection is ensured to get diagnostically meaningful frames that may present critical tumor progression or regressions.

Weighted features Fkey prioritize diagnostic relevant frames for further analysis via equation (3)

$$Fkey = \Sigma(\alpha i * Vi) \quad (3)$$

This mechanism focuses computational resources on key temporal moments, enhancing interpretability for recurrence predictions. For multiple scale feature fusion, the weighted features Fkey are processed through a Feature Pyramid Network (FPN) integrated with UNet process. Multiple scale representations capture global and fine- grained spatial features critically for assessing residual tumor boundaries. The aggregated features Fp are decoded into segmentation masks Ms via UNet.

For the process, a temporal progression function is defined to quantify the tumor progression and predict recurrences. The DSC over temporal instance sets is computed as a measure of the overlap between predicted segmentations Ms and ground truth MGT via equation (4)

$$DSC(t) = \frac{2 * |Ms(t) \cap MGT(t)|}{|Ms(t)| + |MGT(t)|} \quad (4)$$

Te temporal derivative of DSC evaluates changes in tumor volume over temporal in- stance sets. via equation (5)

$$\frac{d}{dt} DSC(t) = lim\ \Delta t \to 0 \left[\frac{DSC(t + \Delta t) - DSC(t)}{\Delta t}\right] \quad (5)$$

Negative values indicate that a tumor grows or recurs whereas the positive value reflects regressions. The model uses temporal gradient and spatial variance of the masks segmentation to define the recurrence risk functions,

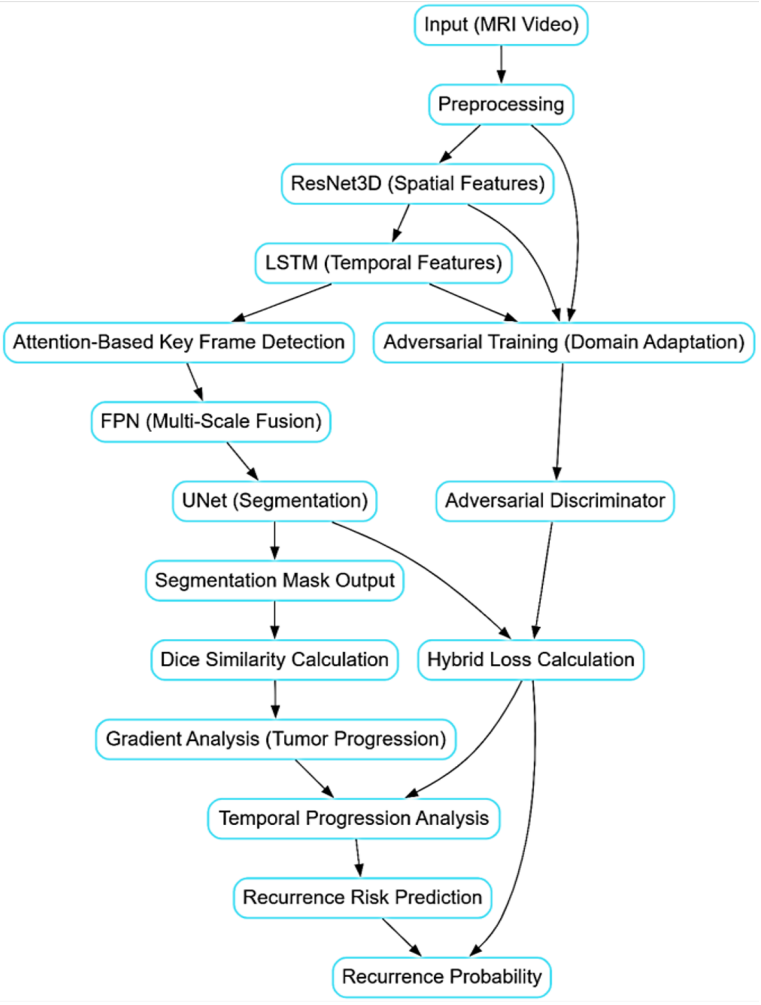

Fig. 1. Model Architecture of the Proposed Analysis Process

For training optimization, this uses a hybrid loss function in the process. The four losses constituted are Dice Loss (LDice), Focal Loss (LFocal), Temporal Consistency Loss (LTemp), and Prognostic Consistency Loss (LProg) via equation (6),

$$LHybrid = \lambda 1\, LDice + \lambda 2\, LFocal + \lambda 3\, LTemp + \lambda 4\, LProg \quad (6)$$

Where λ1, λ2, λ3, λ4 control the relative contributions of each term in the process. Tem-poral consistency penalizes segmentation fluctuations, while prognostic consistency ensures accurate prediction of recurrence. Finally, domain adaptation is implemented via adversarial training to ensure sturdiness across diverse patient data samples. The final recurrence prediction is computed using the sigmoid-normalized risk Function.

By assuring detailed tumor evolution examination, recurrence calculation and strong simplification, this iterative design proposes a comprehensive method to post treatment prognostic examination. We also discuss the effectiveness of the proposed model in terms of different metrics and compare it with existing methods under dissimilar situations.

5 Comparative Result Analysis

A comprehensive experimental model is developed to validate the efficiency of the proposed hybrid DL architecture in performing precise segmentation and modeling spatial–temporal tumor dynamics, whilst approximating recurrence risk from longitudinal brain MRI data. The estimation uses multi-temporal MRI sequences attained from well-known open-access repositories, with main experimentation directed using the Brain Tumor Segmentation (BraTS) benchmark dataset. The experimental dataset comprises roughly 250 longitudinal MRI sequences, each embracing multiple attainments composed across diverse clinical stages, with both pre-therapeutic and post- intervention scans. Every sequence initially comprised of close to 100 frames; though, a static temporal sampling strategy is accepted, where 40 representative frames are consistently and carefully chosen from individual sequence to guarantee temporal alignment across samples. All frames are rescaled to an undeviating spatial determination of 256 × 256 pixels**.** Intensity values are standardized on a per sequence basis to the [0, 1] interval. To boost robustness and avoid overfitting, training samples undergo stochastic augmentation processes, with spatial cropping, rotational perturbations within ±15°, and measured strength dissimilarities up to ±10%.

The dataset is also segregated into training, validation, and testing subsections following a 70:15:15 fragments. Main attention is also given to maintain variability across tumor morphology, pathological classes (e.g., gliomas and meningiomas), and patient demographics within each subset.

All experimentations are executed in the PyTorch framework and executed on an NVIDIA A100 GPU equipped with 40 GB memory specification. Spatial depiction learning is accomplished using a 50-layer 3D residual network employing 3 × 3 × 3 convolutional kernels, producing 512- dimensional feature embeddings for each temporal slice. Temporal evolution patterns are demonstrated using a Long Short- Term Memory (LSTM) module comprising 256 hidden components, permitting the capture of long- range dependencies across the short time frames.

An attention-driven based Transformer encoder is combined to classify temporally salient frames that contribute most suggestively to diagnose interpretation. The module is shaped with 8 self-attention heads, comprising a key dimensionality of 64, and a dropout probability 0.1. For subdivision, a multi-scale decoding strategy is implemented through a Feature Pyramid Network (FPN) attached with a UNet-based decoder.
The course of producing dense separation masks at the original spatial resolution comprises the progressive combination of features aggregated from multiple scales of a pyramid structure. The process is optimized using a multifaceted objective function being utilized, this combines Dice loss, Focal loss, and Temporal Consistency loss in a weighted manner, with coefficients of 0.5, 0.3, and 0.2, correspondingly. Starting learning rate of 1×10^{-3}, 8 sequences as a batch size, and a cosine annealing schedule that spans 100 epochs is utilized in the Adam optimization procedure.

The proposed framework that combines a domain adaptation strategy rooted in Adversarial learning, also moderating the impact of distribution shifts between dataset. This involves training a discriminator, containing three fully linked layers with ReLU triggering, to reduce the inconsistency between the feature distributions of the source and target provinces. This increases the model's capability to simplify across domains using a range of quantitative metrics such as classification accuracy, Dice Similarity Coefficient (DSC). Specifically, the proposed framework gives a classification accuracy of 96.4% and a DSC of 0.91, while maintaining a temporal variance of less than 0.02, which indicates constant partitioning over time. Fig. 2 indicates that the proposed model beats present state-of-the-art methodologies emphasizing its dominance in this regard.

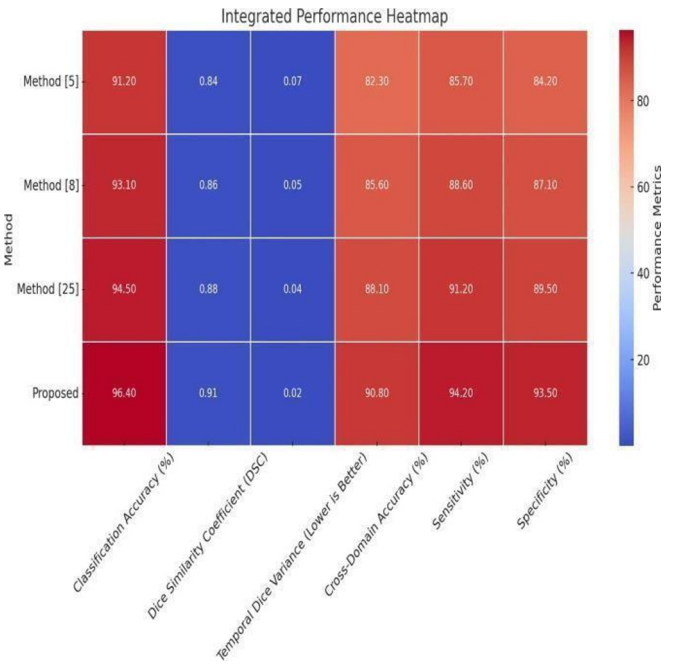

Fig. 2. Model's Integrated Result Analysis

Visible inspection of segmentation outputs, it is observed that it settles precise description of challenging tumor edges and steady pursuing of volumetric instabilities. Additionally, the framework gives tumor recurrence with the precision rate of 94.2%**,** based on altered temporal trends and development patterns.

The BraTS dataset attends as the essential standard for this framework as it includes detailed expert observations. It gives MRI scans containing T1-weighted, divergence-improved T1, T2-weighted, and FLAIR sequence from over 500 patients, with voxel-level labels for tumor sub- sections like processing tumor, tumor core, and complete tumor. Result proves the given framework's correctness for real world clinical decision clinical decision support in brain tumor management.
All MRI section must experience a regular preprocessing channel that includes skull removal and spatial registration to a common structural reference space. Voxel gaps are resampled to an isotropic resolution of 1 mm^3**,** allowing continuous volumetric investigation about studies. The succeeding levels have a spatial size of 240 × 240 × 155, which spheres inclusive three-dimensional tumor morphology decisive for precise discovering and sectioning.

The remarks given by the expert regarding imaging data provide base reality for both training and endorsement phases. As well as imaging labels, the dataset covers relevant clinical metadata, as well as patient's history such as age, tumor ranking information,

and endurance statistics. Such supplementary proof encourages persisted research into prognostic framework and tumor repetition assessment.

Table 1 gives classification appropriateness in distinguishing tumor from non- tumor regions**.** The proposed method gets an accuracy of 96.4%**,** outclassing Liu *et al.* **(**91.2%), Singh and Lobiyal **(**93.1%**),** and Khaliki and Başarslan **(**94.5%**).** This development is accredited to the valuable integration of three-dimensional spatial feature abstraction and temporal dependency exhibiting served by the ResNet3D– LSTM model.

The vigorous categorization presentation indicates the framework's correctness for real time clinical dissemination where high diagnostic stability is risky. The projected system has the impending to sustenance early-stage distinguishing and increase clinical decision-making during treatment organizing by reducing false-positive and false- negative forecasts.

Table 1. Accuracy Comparision

Method	Classification Accuracy (%)
Liu et al. (2024)	91.2
Singh and Lobiyal (2023)	93.1
Khaliki and Başarslan (2024)	94.5
Proposed	96.4

By means of the Dice Similarity Co- efficient (DSC), the subdivision results are quantitatively assessed which imitates the degree of agreement between the anticipated subdivision results and the matching ground truth masks. As displayed in Table 2, the predicted model undertakes a DSC value of 0.91, showing a high level of intersection and segmentation correctness.

Result represents that this performance is better compared to the running methods, as well as the methodologies given by Liu *et al.* (2024), Singh and Lobiyal (2023) and Khaliki and Başarslan (2024). The result enrichment can be credited to the approach used by the FPN–UNet decoder, which accurately combines both localized boundary verification and broader proper interpretations of tumor area.

Tasks such as tumor volumetric assessment, morphological calculation, and assessment of operational changes over time are supported by subdivision of this level. These abilities are specifically imperative for treatment analysis, decision making for surgical task, and observing tumor response during therapy.

Table 2. DSC for Tumor Detection

Method	Dice Similarity Coefficient (DSC)
Liu et al. (2024)	0.84
Singh and Lobiyal (2023)	0.86

Khaliki and Başarslan (2024)	0.88
Proposed	0.91

Dice variance is calculated to measure Temporal dependability, where low values give more loyal subdivision performance throughout successive frames. Table 3 shows corresponding results. The projected model gains the lowest Dice variance of 0.02, indicating superior performance compared with Liu *et al.* (2024), Singh and Lobiyal (2023, and Khaliki and Başarslan (2024)**.**

The enhanced steadiness gives the presence of a Temporal Steadiness Loss. The model maintains coherent tumor boundaries all over during the sequence by implementing even temporal transitions. In real time, such temporal consistency is predominantly perilous and clinical monitoring, where continuous tracking of tumor development is required during therapy.

Table 3. Stability Analysis

Method	**Temporal Dice Variance (Lower is Bet- ter)**
Liu et al. (2024)	0.07
Singh and Lobiyal (2023)	0.05
Khaliki and Başarslan (2024)	0.04
Proposed	0.02

Experimental results establish that high accurateness, temporal consistency, and computational efficiency for brain tumor examination is delivered by the proposed model.

6 Conclusion

A Hybrid deep learning framework for brain tumor presence, subdivision, and recurrence prediction using MRI video sequences is proposed in this paper. The proposed research provides spatio-temporal representation learning through a ResNet3D–LSTM backbone, attention-based key frame selection, multi- scale feature aggregation via an FPN–UNet architecture. Surveying real-world utilizatio n challenges, the model attains a cross-domain accuracy of **96.4%,** focusing toughness against variations in imaging devices and patient demographics. In short, the overall results show that the proposed research efficiently supports early diagnosis, proper treatment planning, and continuous tumor progression monitoring, thereby giving a expressive ability for real-world clinical acceptance.

7 Future Scope

The proposed framework gives better performance, but there are still several research directions remaining for further improvement. One important extension includes mixing of diffusion-weighted imaging (DWI) or positron emission tomography (PET), which could allow richer characterization of tumor heterogeneity and metabolic behavior improving

diagnostic accuracy and recurrence prediction.

The inclusion of patient- specific clinical information, containing genetic markers, molecular profiles, and treatment history is the further future path. Including such metadata would allow the framework to produce personalized predictions and uphold adaptive treatment planning, aligning with the principles of precision medicine.

References

1. A. A. Abdelrahman, Y. A. Kamani, S. K. Patel, A. Armghan, and A. H. M. Almawgani, "Design and investigation ofmachine learning– optimized surface plasmon res- onance biosensor for early brain tumor detection," *Plasmonics*, vol. 20, pp. 5069–5089, 2024.
2. E. Albalawi, T. R. M., A. Thakur, V. V. Kumar, M. Gupta, S. B. Khan, and A. Almushar- raf, "Integrated approach of federated learning with transfer learning for classification and diagnosis of brain tumor," *BMC Med. Imaging*, vol. 24, 2024.
3. S. A. Alshowarah, " DeepCancer: Deep learning for brain tumor detection-based application system," *Neural Comput. Appl.*, vol. 37, pp. 5577–5596, 2025.
4. V. Anitha,"Brain tumor detection in combined 3D MRI and CT images using dictionary learning- based segmentation and Spearman regression," *Sādhanā*, vol. 49, 2024.
5. B. Babu Vimala, S. Srinivasan, S. K. Mathivanan, J. Mahalakshmi, P. Jayagopal, and G. T. Dalu, "Detection and classification of brain tumor using hybrid deep learning models," *Sci. Rep.*, vol. 13, 2023.
6. S. Biradar and Virupakshappa, "AG-MSTLN-EL: A multi-source transfer learning approach to brain tumor detection,"*J. Imaging Inform. Med.*, vol. 38, pp. 245–261, 2024.
7. S. Das and R. S. Goswami, "Advancements in brain tumor analysis: A comprehensive review of machine learning, hybrid deep learning, and transfer learning approaches for MRI-based classifi- cation and segmentation," *Multimedia Tools Appl.*, vol. 84, pp. 26645–26682, 2024.
8. Y. P. Singh and D. K. Lobiyal, "A comparative analysis and classification of cancerous brain tumors detection based on classical machine learning and deep transfer learning models," *Multimedia Tools Appl.*, vol. 83, pp. 39537–39562, 2023.
9. W. Huang and Z. Dai, "Predicting brain tumor presence using machine learning models," *Mul- tiscale Multidiscip. Model. Exp. Des.*, vol. 8, 2024.
10. D. E. Imbaquingo-Esparza, M. Botto-Tobar, J. G. Jacome-Leon, and M. Zambrano-Vizuete, "Exploring advanced deep learning paradigms for precise brain tumor categorization," *SN Comput. Sci.*, vol. 5, 2024.
11. M. Z. Khalikiand M. S. Başarslan, "Brain tumor detection from images and comparison with transfer learning methods and 3-layer CNN," *Sci. Rep.*, vol. 14, 2024.
12. K. Kumar, K. Jyoti, and K. Kumar, "Machine learning for brain tumor classification: Evaluating feature extraction and algorithm efficiency," *Discover Artif. Intell.*, vol. 4, 2024.
13. Y. Liu, Z. Wang, Y. Xue, N. Cheng, B. Shen, L. Hou, and L. Jin, "MRI brain tumor classification based on CNN features and machine learning classifiers," *J. Ambient Intell. Humanized Comput.*, vol. 16, pp. 233–242, 2024.
14. S. M., B. V. Babu, D. Prakash, A. K. Suresh, S. K. Mathivanan, and M. A. Shah, "Efficient brain tumor grade classification using ensemble deep learning models," *BMC Med. Imaging*, vol. 24, 2024.
15. M. A. Maizer and B. Alhijawi, "Temporal brain tumor progression tracking using deep learning and 3D MRI volume analysis," *Int. J. Inf. Technol.*, vol. 16, pp. 3677–3682, 2024.
16. Z. Mansur, J. Talukdar, T. P. Singh, and C. J. Kumar, "Deep learning- based brain tumor image analysis for segmentation," *SN Comput. Sci.*, vol. 6, 2024.
17. A. M. J. Zubair Rahman, M. Gupta, S. Aarathi, T. R. Mahesh, V. V. Kumar, S. Y. Kumaran, and S. Guluwadi, "Advanced AI-driven approach for enhanced brain tumor detection from MRI images utilizing EfficientNetB2 with equalization and homomorphic filtering," *BMC Med. Inform. Decis. Mak.*, vol. 24, 2024.
18. 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
19. K. M. Hosny, M. A. Mohammed, R. A. Salama, and A. M. Elshewey, "Explainable ensemble deep learning-

based model for brain tumor detection and classification," *Neural Comput. Appl.*, vol. 37, pp. 1289– 1306, 2024.