Brain Cancer Detection Research Papers Summary

Title	Dataset Name and URL	Dataset Description	Methods Name	Accuracy	Research Questions	Pros and Cons	Citation
Brain Tumor Detection Based on Deep Learning Approaches and Magnetic Resonance Imaging	Kaggle Brain Tumor MRI Dataset	10,288 images. Classes: Glioma (2548), Pituitary (2658), Meningioma (2582), No tumor (2500). Split: 80% training (8232), 20% testing (2056).	Refined YOLOv7 with CBAM attention, SPPF+, BiFPN, and decoupled heads.	99.5%	Can a fine-tuned YOLOv7 model accurately detect and precisely locate multiclass brain tumors? How can small-size brain cancers be better detected?	Pros: High accuracy; precise tumor localization via bounding boxes; low computational cost. Cons: Bounding boxes may capture non-tumor tissue; tedious labeling process; lacks validation on actual clinical data.	Abdusalomov, A.B.; Mukhiddinov, M.; Whangbo, T.K. Brain Tumor Detection Based on Deep Learning Approaches and Magnetic Resonance Imaging. Cancers 2023, 15, 4172.
Classification of Brain Tumor from Magnetic Resonance Imaging Using Vision Transformers Ensembling	Figshare brain tumor dataset	3064 T1w CE MRI slices from 233 patients. Classes: Meningioma (708), Glioma (1426), Pituitary (930). Split: 70% training (2137), 10% validation (314), 20% testing (613).	Ensemble of four Vision Transformer (ViT) models (B/16, B/32, L/16, L/32).	98.7% (at 384x384 resolution)	Does an ensemble of standard ViT models outperform individual models and traditional CNNs in diagnosing brain tumors from MRI?	Pros: Superior to custom CNNs; ensemble approach increases overall accuracy; robust across hyperparameter settings. Cons: High computational demand (requires TPUs); feature overlapping can cause misclassification.	Tummala, S.; Kadry, S.; Bukhari, S.A.C.; Rauf, H.T. Classification of Brain Tumor from Magnetic Resonance Imaging Using Vision Transformers Ensembling. Curr. Oncol. 2022, 29, 7498-7511.
A fine-tuned vision transformer based enhanced multi-class brain tumor classification using MRI scan imagery	Combination of Figshare, SARTAJ, and Br35H	7,023 images. Classes: Glioma, Meningioma, Pituitary, and No tumor. Split: 5,712 images for training, 1,311 for testing.	Fine-Tuned Vision Transformer (FTVT) models with custom classifier heads (BN, Linear, ReLU, and Dropout layers).	98.70% (achieved by FTVT-l16)	How do FTVT models compare with established deep learning models like ResNet50 and EfficientNet-B0 in multi-class classification?	Pros: Custom classifier head allows for task-specific representations; '16' variant models capture finer details; higher accuracy than standard CNNs. Cons: Large variants require more computational resources; some misclassification in the meningioma class.	Reddy, C.K.K.; et al. A fine-tuned vision transformer based enhanced multi-class brain tumor classification using MRI scan imagery. Front. Oncol. 2024, 14:1400341.
A review of deep learning for brain tumor analysis in MRI	Multiple public datasets including BraTS, NYUMets, and Figshare	Reviews multiple sources. Figshare: 233 patients (Glioma, Meningioma, Pituitary). BraTS 2021: 2000 patients (Adult diffuse glioma).	Synthesizes various models: CNNs (U-Net, ResNet), Vision Transformers, and Foundation Models.	N/A (Review paper summarizing SOTA results, e.g., BraTS ensembles achieving ~0.92 Dice score)	What are the existing applications, limitations, and future transformative potentials of deep learning for brain tumor segmentation and classification?	Pros: Comprehensive outlook; identifies potential for personalized medicine and foundation models; objective measurements. Cons: Models are often 'black-boxes'; significant challenges in site generalization and clinical translation.	Dorfner, F.J.; et al. A review of deep learning for brain tumor analysis in MRI. npj Precis. Onc. 2025.

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Advancing Brain Tumor Classification through Fine-Tuned Vision Transformers	Kaggle Brain Tumor MRI Dataset	5,712 images. Classes: Glioma (1321), Meningioma (1339), No tumor (1595), Pituitary (1457). Split: 4855 training, 857 testing.	Five Fine-tuned Vision Transformer (ViT) models (R50-ViT-l16, ViT-l16, ViT-l32, ViT-b16, ViT-b32).	98.24% (achieved by ViT-b32)	Can fine-tuning pre-trained ViT models improve performance over existing approaches? Which ViT variant is most effective for this task?	Pros: Effectively captures global pixel relationships; outperforms several existing state-of-the-art methodologies. Cons: Computationally expensive to train and deploy; some variants show signs of overfitting.	Asiri, A.A.; et al. Advancing Brain Tumor Classification through Fine-Tuned Vision Transformers: A Comparative Study of Pre-Trained Models. Sensors 2023, 23, 7913.