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A Survey on Machine Learning and Deep Learning Techniques for Brain Tumor Detection in MRI Images

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***Abstract*—Malignant tumor detection using human image evaluation which are bound to human errors and time consuming. MRI (Magnetic Resonance Imaging) image tool has become an important tool to locate the brain tumors as brain tumors can be detected in various stages of development which vary in size and can be located in any part of the brain. Detecting Brain-Tumor using MRI is a crucial task in medical diagnosis, where early and accurate identification helps the patients. Over the past decade, machine learning and deep learning techniques have been widely adopted for automated tumor detection, segmentation, and classification. This paper provides us with a literary survey of existing approaches, including preprocessing techniques, segmentation methods, feature extraction strategies, optimization algorithms, and classification models.**

The survey highlights the strengths and weaknesses of traditional machine learning models, deep learning architectures, and hybrid frameworks. Special attention is given on feature fusion techniques and optimization strategies that enhance model performance. In spite of achieving high accuracy, current approaches face limitations such as static feature fusion, lack of adaptability, and absence of uncertainty modeling. This paper identifies key research gaps and outlines future directions toward developing adaptive, robust, and intelligent brain tumor detection systems.

***Index Terms*—Brain Tumour Detection, Convolutional Neural Network, Deep Learning, Machine Learning, MRI**

I. INTRODUCTION

According to Global Brain Tumor Statistics 2025 (GLOBOSCAN (IARC) and Global Burden of Disease) approximately 2,50,000 people die from cancer and an estimation of 3,50,000 to 3,57,000 new cases had been identified. The abnormal growth and multiplication of cells in the brain region is identified as Brain Tumor. The tumor induced in the brain can cause health concerns such as Seizures, Sensory loss, Memory loss, Hydrocephalus, etc., Location of the tumor and its size determine the severity and treatment options.

Brain tumor is widely classified into two categories-Benign and Malignant. Benign is an abnormal growth of cells within the brain or central nervous system (CNS) that is not cancerous. They lack the aggressive, invasive nature of malignant tumors like glioblastoma, and they also present significant medical challenges. Malignant is a cancerous and aggressive growth of cells within the brain or central nervous system. These tumors are highly aggressive and can invade surrounding healthy brain tissue, making them far more dangerous than non-malignant masses. Primary brain tumors can be benign or malignant or both while secondary brain tumors are malignant and spread to body parts causing severe health problems (Soomro et al, 2022).

Deducing the tumor in the early stages will have a huge impact on the severity and treatment of the tumor. Magnetic Resonance Imaging (MRI) captures brain images in axial, coronal and sagittal sections. The MRI images are produced in high resolution and offer great contrast of details of the brain (Fink et al., 2015). Advancement in machine learning, deep learning and image processing methods has restructured object classification, decision making and cancer detection. To detect tumors with a wide range of patient data, machine learning and deep learning methods have emerged. The accurate detection of brain tumors using machine learning models depends on the learning capabilities that are fine tuned to understand the features which are relevant and discriminating power of the models (Abdusalomov et al., 2023).

The accuracy of the introduced machine models is majorly dependent on the extracted features from the image and its ability to map the tumor (Amin et al., 2020). The accuracy and performance of these models depend on the quality and quantity of the provided data. Each machine learning model has its own learning capability that cannot be generalized to one single problem. Researchers use different techniques in each step in the image processing model to achieve maximum accuracy and performance. The process of developing a machine learning model for tumor detection involves preparation of the data, feature selection, model selection, training the model, testing the model, model evaluation and deployment (Zeng, et al., 2024).

This paper is organized into three sections, Section I gives an introduction to tumor detection, Section II discusses the recent literature on tumor detection using machine learning models and section III concludes the paper.

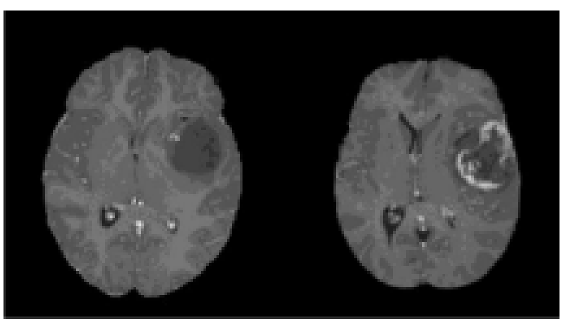

Figure 1: Example MRI Image

II. LITERATURE REVIEW

1. (Abdusalomov et al., 2023) applied a multi-stage deep learning pipeline to propose a high accuracy system based on a refined YOLOv7 (You Only Look Once version 7) architecture to identify three major types of tumors. This architecture has achieved an accuracy of 99.5%, making it a powerful decision-making tool. They used an open access MRI dataset which contains 2,548 gliomas, 2,658 pituitary tumors, 2,582 meningiomas, and 2,500 non-tumor images. The refined YOLOv7 architecture contains Convolutional Block Attention Module (CBAM) to enhance feature extractions, Spatial Pyramid Pooling Fast+ (SPPF+) to improve model's sensitivity, Bi-directional Feature Pyramid Network (BiFPN) to increase multi-scale feature fusion and Decoupled heads for an efficient extraction of useful insights from a vast variety of data. This model has achieved a superior accuracy of 99.5%, significantly faster inference for real-time clinical work and the usage of CBAM and BiFPN allows the model to learn subtle features and contextual patterns which might be missed by human expertise. This model depends on the quality and diversity of the training data set. Infiltrative tumors like glioblastomas remain a more challenging task. Integration of multiple modules like CBAM, BiFPN etc., requires specialized hardware to achieve the real-time processing speeds.

2. (Lensee at al., 2021) developed nnU-Net (no-new-net) which is a self-configuring framework that adapts the entire segmentation pipeline to any new dataset. The algorithm extracts the properties of data such as image size, voxel spacing and class ratios. Based on the hardware and data it automatically selects 2D U-Net, 3D U-Net and U-Net Cascade, a two-stage process. It uses heuristic rules to data-dependent parameters. It preserves robust defaults. It is often an ensemble of 2D and 3D models and it automatically removes the blobs in the post processing. This model always achieves against the modalities like MRI, CT and Electron Microscopy and the model is fully automated. Computation requires high GPU resources and can take several days. The speed is slow during 'test-time' compared to single pass models. This model can struggle with datasets which have extreme anisotropy or very low signal. This model lacks Architectural Intelligence.

3. (Zeng et al., 2024) have provided a detailed study on Machine Learning especially Deep Learning to highlight the clinical value of AI-

Detection in identifying Lesions, Tumors and Fractures. The methodology used here to extract features is Convolutional Neural Network (CNN) and in this model AI is integrated with CT imaging for pneumonia analysis. The high efficiency due to the usage of AI, detecting 'tiny lesions' which can be omitted by human eye and consistency, reducing human errors serves as advantages. Standardized Acquisition Protocols are not found across different hospitals, leading to variations in equipment settings, degrading the model performance. They face privacy and ethical issues. "Black Box" challenge, where the doctors fail to understand the reason behind the model's predictions, becomes the biggest disadvantage.

4. (Anantharajan et al., 2024) proposed a brain tumor detection method based on deep learning and machine learning. The proposed models consist of a deep neural network and support vector machine. The Neural network consists of three layers which filters the features and passed to SVM. The performance of the proposed model achieved accuracy of 97.93 %, sensitivity of 92 % and specificity of 98 %. Initially the images are preprocessed with Adaptive Contrast Enhancement Algorithm (ACEA) and median filter followed by segmentation using Fuzzy c-means.

5. (Amin et al., 2024) proposed a pipeline that fuses deep learning features with hand crafted features, capturing both high level semantic context provided by deep neural networks and the structural nuances identified by traditional image processing techniques. The Grab Cut method is used to accurately isolate actual lesion symptoms. CNNs such as VGG-16, VGG-19 or ResNet are fine tuned to extract high-dimensional deep features. The system extracts classical features. The system extracts classical features related to shape and texture using LBP or HOG Descriptors. Support Vector Machines or LSTM networks are used to categorize the images into specific tumor types or non-tumor cases. The model has reached an accuracy above 90%. Location, shape and intensity of the tumor can be identified. This model faces computational complexity. Performance depends on the quality and quantity of the training data. To maintain efficiency, additional features might be required.

6. (Khan et al., 2024) authors developed a hybrid framework called Hybrind-Net which amplifies the capabilities of DenseNet169. This model has given an accuracy 95.10%. This model utilizes machine learning classifiers such as Support Vector Machines (SVM), Random Forest (RF), XGBoost. This framework is specialized at handling the heterogenous structure and complex morphology of brain tumors. This methodology requires a proper functioning of both the deep learning feature extractor and the various machine learning classifiers.

7. (Bhimavarapu et al., 2024) has published a paper which is designed for the precise identification and categorization of tumors. This model utilizes an unsupervised clustering approach for segmentation and a machine learning classifier for detection. The system achieves an accuracy of 98.56% outperforming existing models by approximately 1.2% to 6.2%. The core of the pipeline is an improved Fuzzy C-Means clustering algorithm. The final diagnosis is done by an improvised Extreme Learning Machine (ELM). This methodology has been tested with the datasets: Figshare (achieving 98.47% accuracy) and Kaggle (achieving 99.42% accuracy.). High accuracy has been absorbed in directing Glioma grades. Reduction in human error and it is cost and time efficient. The proposed model faces Computational Complexity. Feature selection plays a vital role in determining the quality of the final diagnosis.

8. (Liu et al., 2022) authors propose a two-stage framework that uses both pixel-level and feature-level fusion to achieve a finer and more pathological-aware segmentation. This model uses a Pixel-level Fusion (PIF-Net) to fuse 3D Multimodal images. Modality Selection Feature Fusion (MSFF) is designed to refine multimodal features. These two methodologies are integrated into the V-Net model. The combination of the two proposed models has improved the

segmentation accuracy. This model has architectural complexity. When the registration is imperfect, its performance may degrade.

9. (Kabir et al. 2025) authors propose a Bayesian deep segmentation model specifically designed to delineate Glioblastoma (GBM) sub-regions, such as FLAIR hyperintensity, enhancing tumor, and central necrosis, while accounting for these post-therapeutic structural shifts. The major methodology is the integration of Bayesian Deep Learning to assess the uncertainty of predictions. The datasets used for training are 311 follow-up MRIs acquired after treatments. Dice Similarity Coefficient (DSC) is used to achieve high scores. This framework is specialized for the post-surgical brain. Follow-up scan is vital for evaluating treatment response. The One-Size-Fits-All model does not work for GBM assessment.

10. (Asghar et al. 2025) authors introduced the HAAU-Net framework which integrates context-aware morphological features with a hybrid attention mechanism. This achieves an accuracy of 96.8%. Multi-scale Adaptive Attention Blocks (AAB) allow to integrate local texture details. Context-Aware Morphological Feature Module (CAMFM) maintains the stability of morphological features. Spatial-Channel Hybrid Attention Mechanism (SCHAM) filters out unwanted features. The dataset used is the BraTS 2023/22 dataset using T1, T1GD, T2, and T2-FLAIR sequences. This model achieved a Dice Coefficient of 0.89. Computational complexity is reduced by 43% increasing efficiency. The proposed methodology achieves a processing speed of 28 frames per second on a standard GPU. Diffusion Weighted Imaging (DWI) is not included. A high source of GPU is required.

11. (Kannan et al..2025) authors proposed the UADAT-Net (Uncertainty-Aware Dual Attention Tumor Segmentation Network) framework which helps to overcome ‘classic problems’ and provide precise segmentation. This methodology uses Adaptive Neuro-Fuzzy Contrast Harmonization to improve image contrast. The core network utilizes Channel Attention, Spatial Attention, and Bayesian Uncertainty Modeling to delineate precise boundaries and improve overall robustness. Hybrid Spatial-Spectral Tumor Representation Learning is used to extract discriminative features. A Self-Regularized Ensemble Capsule Network performs the final categorization. It employs Groupers and Moray Eels–based Hyperparameter Tuning to ensure stable convergence and select optimal model parameters. The proposed framework achieves high performance with 98.90% accuracy on MRI and 99.20% on Figshare datasets. The proposed model faces architectural complexity. Performance relies heavily on the successful execution of the complex GME-HT hyperparameter optimization phase.

TABLE 1 SUMMARY OF LITERATURES DISCUSSED

Author	Methodology	Performance Metrics	Advantages	Disadvantages
Abdusalomov et al. (2023)	Refined YOLOv7 (CBAM, SPPF+, BiFPN, Decoupled heads).	99.5% Accuracy.	High accuracy and fast inference for real-time clinical use.	Dependent on data quality; struggles with infiltrative glioblastomas.
Isensee et al. (2020)	nnU-Net: Self-configuring framework (2D, 3D, and Cascade variants).	Benchmark winner for BraTS 2020.	Fully automated; high robustness across diverse modalities (MRI, CT).	High GPU resource requirements; lacks explicit attention-based architectural intelligence.
Zeng et al. (2024)	CNN-based feature extraction and AI	Highlighted clinical value in	High efficiency; identifie	"Black-box" interpretability gap;

	integration with CT imaging.	lesions/tumors.	s "tiny lesions" often missed by human experts.	lacks standardized acquisition protocols.
Anantharajan et al. (2024)	ACEA + Median filter (Preprocessing), FCM (Segmentation), DNN + SVM (Classification).	97.93% Accuracy; 98% Specificity.	Robust filtering and multi-stage classification pipeline.	Dependent on data quality.
Amin et al. (2024)	Hybrid Fusion: CNN (VGG/ResNet) + Hand-crafted features (LBP/HOG).	>90% Accuracy.	Captures both high-level semantic context and structural nuances.	High computational complexity; requires additional feature selection for efficiency.
Khan et al. (2024)	Hybrid-NET: DenseNet169 backbone + SVM/RF/XGBoost classifiers.	95.10% Accuracy.	Handles heterogeneous structures and complex tumor morphology.	High sensitivity to hyper-parameter tuning of the feature extractor.
Bhimavarapu et al. (2024)	Improved FCM (Segmentation) and Improved ELM (Classification).	98.56% Accuracy.	Precise identification of glioma grades; cost and time-efficient.	High computational power required for segmentation; sensitive to
				image artifacts.
Liu et al. (2022)	Two-stage Framework: PIF-Net (Pixel-level) + MSFF (Feature-level) in V-Net.	Improved segmentation accuracy.	Pathological-aware segmentation with dynamic modality weighting.	Increased architectural complexity; highly sensitive to registration errors.
Kabir et al. (2025)	Bayesian Deep Learning + Transfer Learning for follow-up MRIs.	0.931 DSC for necrosis.	Specialized for post-surgical brains; identifies uncertainty in structural shifts.	One-size-fits-all models fail for GBM assessment; requires manual dependency.
Asghar et al. (2026)	HAAU-Net: Hybrid Adaptive Attention U-Net (AAB, CAMFM, SCHAM).	96.8% Accuracy; 28 FPS.	Reduces complexity by 43%; capable of real-time clinical deployment.	Performance is dependent on modal preprocessing; it requires high GPU resources.
Kannan et al. (2025)	UADAT-Net: ANFCH, Dual Attention, and Bayesian Uncertainty Modeling.	98.90% Accuracy (MRI).	Solves "classic problems" (low contrast) and provides reliable boundaries.	High architectural complexity; performance heavily relies on GME-HT optimization.

III. CONCLUSION

Brain tumor detection through computer aided diagnosis (CAD) has an important role in diagnosing and saving lives from malignant brain tumors. The development of advanced technologies such as machine learning and artificial intelligence has given rise various opportunities in medical diagnosis. Many machine learning models such as KNN, SVM, RF and NN are used for brain tumor detection. Techniques such as pre-processing, segmentation play an important role in enhancing the classification model performance.

Feature extraction techniques have become an integral part of MRI images diagnosis. Understanding the features, extracting relevant features help classifiers to distinguish various forms of brain tumors in MRI images. Also, deep learning models and transfer learning models are widely used in brain tumor diagnosis for its automatic feature learning, capable of handling large datasets and better decision-making strategies. Though many machine learning models and deep learning models are currently being studied, it is still imperative to address the challenges in brain tumor detection through developing models that fill the gaps in detection accuracy, model complexity and more generalization.

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