



BRAIN TUMOR DETECTION USING MACHINE LEARNING

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Abstract: Brain tumor detection is a critical task in medical imaging that requires timely and accurate diagnosis for effective treatment. Manual interpretation of MRI scans is time-consuming and prone to human error. Machine Learning (ML) and Deep Learning (DL) techniques have demonstrated remarkable performance in automating tumor detection, segmentation, and classification. This review paper provides a comprehensive overview of various ML methods applied to brain tumor detection, discusses datasets, algorithms, evaluation metrics, and highlights recent trends and future research directions. The paper aims to provide a clear understanding of the current state-of-the-art approaches and the challenges that remain in this domain.

Keywords: Brain Tumor, Machine Learning, Deep Learning, MRI, Image Processing

I. INTRODUCTION

Brain tumors are abnormal growths of cells within the brain that may be benign or malignant. Early detection of brain tumors is crucial to improve patient outcomes and reduce mortality rates. Traditional diagnostic approaches rely on manual analysis of MRI or CT scans by radiologists. However, manual interpretation can be subjective, time-consuming, and prone to errors. With advancements in artificial intelligence, Machine Learning (ML) and Deep Learning (DL) have emerged as powerful tools for automating brain tumor detection. These techniques can extract features, segment tumor regions, and classify tumor types with high accuracy. Modern approaches utilize Convolutional Neural Networks (CNNs), Support Vector Machines (SVM), Random Forests (RF), and hybrid models to achieve precise detection and classification.

This paper provides a comprehensive review of the methodologies, findings, and trends in brain tumor detection using ML, aiming to highlight challenges and future directions. Brain tumor detection using machine learning involves applying algorithms to medical images, primarily MRI scans, to automate the identification and classification of tumors, offering faster, more accurate diagnoses than traditional methods. Deep learning, especially Convolutional Neural Networks (CNNs), excels at analyzing these complex images, identifying subtle patterns, and performing segmentation to assist radiologists and improve patient outcomes through timely treatment. Traditional diagnosis of brain tumors relies heavily on medical imaging techniques, particularly Magnetic Resonance Imaging (MRI), Computed Tomography (CT) scans, and Positron Emission Tomography (PET) scans. Radiologists and neurologists manually analyze these images to identify abnormalities, assess tumor characteristics, and plan treatment strategies. However, this manual process is time-consuming, subjective, and prone to human error, especially when dealing with subtle or complex cases.

II. LITERATURE SURVEY

Over the last decade, numerous research studies have focused on improving the accuracy and efficiency of brain tumor detection. Early studies primarily relied on handcrafted features extracted from MRI images, such as texture, intensity, shape, and edge information. Traditional machine learning classifiers like Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Decision Trees, and Random Forests were widely applied for tumor classification. While these methods achieved moderate accuracy, they were heavily dependent on feature selection and pre-processing steps. Recent developments in deep learning have revolutionized brain tumor detection. Convolutional Neural Networks (CNNs) are capable of automatically learning hierarchical features from raw MRI images, eliminating the need for manual feature extraction. Researchers have successfully applied architectures like AlexNet, VGGNet, ResNet, and U-Net for tumor segmentation and classification. Studies report accuracy levels exceeding 95% on standard datasets such as



BRATS (Brain Tumor Segmentation Challenge). Hybrid approaches combining deep learning with classical ML models have also shown improvements in both accuracy and computational efficiency.

Transfer learning techniques, using pre-trained models on large datasets, have further enhanced performance, especially for limited medical datasets. Overall, the literature indicates that deep learning models outperform traditional methods, yet challenges such as data imbalance, overfitting, and lack of interpretability remain prevalent in clinical applications.

III. METHODOLOGY

The process of brain tumor detection using machine learning typically involves several stages:

3.1 Image Acquisition

The first stage is the acquisition of high-quality MRI or CT images. Publicly available datasets like BRATS, along with institutional datasets, are commonly used for training and testing ML

models. 1. Imaging Modalities Used Brain tumor detection relies primarily on MRI (Magnetic Resonance Imaging) because of its high resolution and ability to differentiate soft tissues. Other imaging modalities include CT, PET, and fMRI. MRI (Magnetic Resonance Imaging): Most widely used for brain tumor detection. Produces high-resolution images of soft tissues. Sequences like T1-weighted, T2-weighted, FLAIR, and contrast-enhanced T1 provide different tissue contrasts to highlight tumors. CT (Computed Tomography): Uses X-rays to produce cross-sectional images. Faster and useful for emergency cases, but less effective for soft tissue contrast. PET (Positron Emission Tomography): Shows metabolic activity of tissues using radioactive tracers. Helps in identifying active tumor regions and malignancy. fMRI (Functional MRI): Measures brain activity by detecting blood flow changes. Helps in pre-surgical planning to avoid critical brain regions.

3.2 Preprocessing

Preprocessing is critical to remove noise, normalize intensities, and enhance image quality. Common techniques include histogram equalization, skull stripping, and Gaussian smoothing.

3.3 Segmentation

Tumor regions are segmented from healthy tissues using methods such as thresholding, region growing, clustering, or deep learning-based segmentation models like U-Net. Accurate segmentation is vital for subsequent classification.

3.4 Feature Extraction

Traditional approaches extract statistical, textural, and structural features from segmented tumor regions. Features may include intensity, shape, texture descriptors, and wavelet coefficients. Deep learning models learn features automatically through convolutional layers. Feature extraction is a critical step in brain tumor detection that transforms raw medical imaging data into meaningful, quantifiable characteristics that machine learning algorithms can use for classification and analysis. The goal is to identify and extract relevant patterns, textures, shapes, and intensities that distinguish tumor regions from healthy brain tissue.

3.5. Classification

Extracted features or learned representations are fed into machine learning classifiers such as SVM, Random Forest, or fully connected neural networks for tumor type classification. Deep learning end-to-end models directly output tumor class probabilities.

1. Binary Classification Determines whether a tumor is present or absent in the brain scan. Classes: Tumor Present No Tumor (Normal Brain) Initial screening Quick triage of cases Pre-processing for more detailed analysis
2. Multi-Class Classification Categorizes brain tumors into specific types based on their characteristics. Common Classification Schemes: Primary Brain Tumor Types: Glioma: Tumors arising from glial cells (most common) Meningioma: Tumors of the meninges (usually benign) Pituitary Tumors: Tumors in the pituitary gland No Tumor: Healthy brain tissue Glioma Grading (WHO Classification):

Grade I: Pilocytic Astrocytoma (benign, slow-growing)

Grade II: Low-grade Glioma (diffuse, slow-growing)

Grade III: Anaplastic Glioma (malignant, faster-growing) Grade IV: Glioblastoma (highly malignant, aggressive)

Multi-Label Classification Assigns multiple labels simultaneously (e.g., tumor type, grade, and location). Machine Learning Classification Algorithms Traditional Machine Learning Classifiers 1. Support Vector Machine (SVM) Principle: Finds the optimal hyper-plane that maximally separates different classes in high-dimensional feature space. Characteristics: Effective in high-dimensional spaces Memory efficient (uses subset of training points) Versatile with different kernel functions



1. Evaluation Metrics

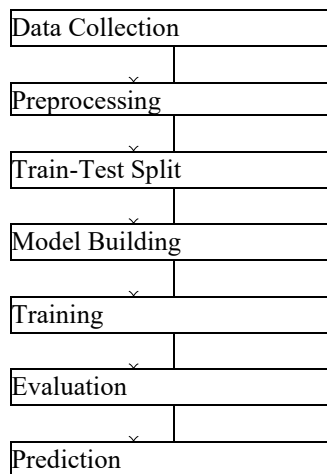
Model performance is evaluated using metrics such as Accuracy, Precision, Recall, F1-Score, Sensitivity, Specificity, and Dice Coefficient. Cross-validation and independent test sets are commonly employed to validate model generalization.

2. Implementation Workflow

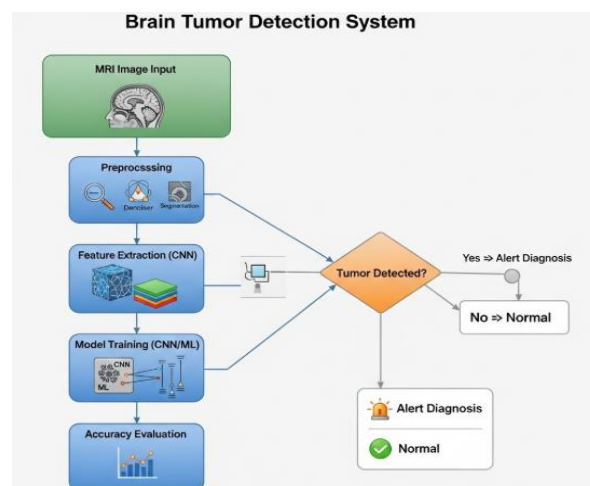
1. Collect MRI images from datasets.
2. Preprocess images for noise reduction and normalization.
3. Segment tumor regions using deep learning or traditional algorithms.
4. Extract features or use CNN for automatic feature learning.
5. Classify tumors into glioma, meningioma, or pituitary categories.
6. Evaluate model performance using appropriate metrics.
7. Optimize model using hyperparameter tuning or transfer learning. This multi-stage methodology ensures a systematic and re- producible approach to brain tumor detection using machine learning.

System Flow Diagram

1. Data Collection → Get MRI images dataset (e.g., Kaggle).
2. Data Preprocessing → Resize images, normalize pixels (0–1), label tumor/no tumor.
3. Train-Test Split → Divide dataset (e.g., 80% training, 20% testing).
4. Model Building → ML models: SVM, Random Forest; DL models: CNN.
5. Training → Model learns from MRI images.
6. Evaluation → Check accuracy, precision, recall, confusion matrix.
7. Prediction → Test on new MRI images.



System Architecture Diagram:





IV. FINDINGS AND TRENDS

- Deep learning models consistently outperform traditional ML classifiers in segmentation and classification tasks. Analysis of existing studies reveals several key findings and emerging trends:
- Transfer learning is increasingly adopted to address the lack of large medical datasets.
- Data augmentation techniques (rotation, flipping, scaling) are widely used to improve model generalization.
- Hybrid models that combine CNNs with classical ML classifiers achieve improved accuracy and robustness.
- Explainable AI (XAI) methods are being integrated to visualize model decisions and improve clinical trust.
- Federated learning frameworks are emerging to allow model training on distributed hospital data while preserving patient privacy.
- Ensemble learning strategies are applied to combine multiple models for better performance.
- Despite high accuracy, challenges such as overfitting, data imbalance, and interpretability remain major concerns. Overall, the field is moving toward highly accurate, interpretable, and clinically deployable brain tumor detection systems.

1. Research is combining multiple distinct deep learning models together to improve accuracy and reliability beyond what single models can achieve Brain tumor detection empowered with ensemble deep learning approaches from MRI scan images | Scientific Reports. Approaches include parallel model integration techniques that merge pre-trained deep learning models Hybrid model integration with explainable AI for brain tumor diagnosis: a unified approach to MRI analysis and prediction | Scientific Reports.

2. Attention Mechanisms and Transformers

Modern architectures integrate attention mechanisms, Graph Attention Networks (GAT), and transformers to extract deeper features and improve model representation, offering interpretable attention maps that expose specific tumor regions Optimized deep learning for brain tumor detection: a hybrid approach with attention mechanisms and clinical explainability - PMC. Vision Transformer (ViT) combined with Gated Recurrent Unit (GRU) models represents an innovative framework for enhanced detection and classification Brain tumor detection and classification in MRI using hybrid ViT and GRU model with explainable AI in Southern Bangladesh | Scientific Reports.

3. Transfer Learning and Fine-Tuning

Researchers are demonstrating that fine-tuning state-of-the-art models like YOLOv7 through transfer learning significantly improves brain tumor detection in MRI scans Brain Tumor Detection Based on Deep Learning Approaches and Magnetic Resonance Imaging - PMC. The Convolutional Block Attention Module (CBAM) is being incorporated into models to further enhance feature extraction capabilities

4. Multi-Modal Feature Extraction

Current research explores synergy among multiple feature representation schemes including Local Binary Patterns, Gabor filters, Discrete Wavelet Transform, Fast Fourier Transform, CNNs, and Gray-Level Run Length features Enhanced MRI brain tumor detection using deep learning in conjunction with explainable AI SHAP based diverse and multi feature analysis | Scientific Reports.

5. Automated End-to-End Frameworks

There's a strong push toward automated methods to replace labor-intensive manual tumor recognition, which remains inefficient and imprecise An automated deep learning framework for brain tumor classification using MRI imagery | Scientific Reports, with researchers developing comprehensive frameworks that handle the entire detection pipeline.

6. Clinical Application Focus

The field is increasingly emphasizing practical clinical deployment, with models designed to assist radiologists in real-time diagnosis and provide survival predictions alongside tumor segmentation.

Would you like more details on any specific trend or information about the techniques being used?

V. CONCLUSION

Machine learning and deep learning techniques have significantly advanced the field of brain tumor detection. Traditional methods relying on handcrafted features and Machine learning and deep learning have revolutionized brain tumor detection, demonstrating remarkable accuracy rates. Studies show that advanced models like ResNet-50 achieve accuracy rates of 96.50%, outperforming other architectures while processing data more efficiently.



Despite impressive accuracy rates, significant challenges remain. For certain tasks like MGMT prediction in the 2021 BraTS challenge, the winning model achieved an AUROC of only 0.62, which is considered poor and certainly not sufficient for reliable clinical decision-making

This technology significantly improves brain tumor diagnosis and treatment accuracy and speed, though results from machine learning still require validation and approval from physicians and healthcare experts. Despite impressive accuracy rates, significant challenges remain. For certain tasks like MGMT prediction in the 2021 BraTS challenge, the winning model achieved an AUROC of only 0.62, which is considered poor and certainly not sufficient for reliable clinical decision-making

VI. FUTURE DIRECTIONS

Future research should focus on integrating multimodal data including MRI, CT, and PET scans to enhance the performance of deep learning models, while investigating transfer learning approaches to adapt pre-trained models for improved precision

In summary, machine learning has demonstrated exceptional promise in automating and improving brain tumor detection with high accuracy rates. Classical classifiers have been largely surpassed by CNN-based approaches capable of automatic feature extraction. Transfer learning and hybrid models have further improved performance, especially when working with limited datasets. Data augmentation, ensemble learning, and explainable AI have emerged as critical trends to enhance model accuracy and interpretability. Despite these advances, several challenges remain, including data scarcity, overfitting, lack of model explainability, and computational resource requirements. Future research should focus on developing clinically deployable models that are accurate, fast, and interpretable. Integrating federated learning for privacy-preserving data sharing, combining multimodal imaging data, and enhancing model transparency will be essential for translating these techniques into real-world clinical applications. With ongoing advancements, machine learning promises to revolutionize brain tumor diagnosis, reduce human error, and ultimately improve patient care. Brain tumor detection using machine learning represents a paradigm shift in medical diagnostics, moving from purely human-dependent analysis to collaborative human-AI systems that leverage the strengths of both computational and clinical intelligence. The technology has matured from theoretical possibility to practical reality, with systems demonstrating clinical-grade performance in controlled settings.

However, the journey from research laboratory to ubiquitous clinical deployment remains ongoing. Success requires continued collaboration among computer scientists, medical professionals, regulatory bodies, and healthcare administrators to address technical, clinical, regulatory, and ethical challenges. The path forward demands not just technological innovation but thoughtful implementation that prioritizes patient welfare, clinical utility, and healthcare accessibility. As the technology continues to evolve, maintaining focus on these fundamental goals while navigating technical and practical challenges will be essential. Brain tumor detection using machine learning is not a replacement for human medical expertise but rather a powerful augmentation of it—a tool that enables earlier detection, more accurate diagnosis, and more efficient healthcare delivery. As these systems continue to develop and integrate into clinical practice, they promise to be instrumental in the ongoing fight against brain cancer, potentially saving countless lives through improved diagnosis and treatment of this devastating disease. The convergence of artificial intelligence and medical imaging represents one of the most promising frontiers in modern medicine. As we continue to refine these technologies, expand datasets, improve algorithms, and deepen our understanding of both machine learning and brain tumors, we move closer to a future where every patient, regardless of location or resources, has access to world-class diagnostic capabilities. This democratization of medical expertise through technology represents not just a scientific achievement, but a step toward a more equitable and effective global healthcare system.

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