Brain Tumor Detection using ML and DL Approaches: A Comparative Review of Models and Methods

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Abstract:
One of the most deadly neurological disorders is brain tumors, and prompt and accurate diagnosis is necessary to plan appropriate treatment. Recent years have seen the development of algorithms for machine learning (ML) and deep learning (DL) that are helpful in automatically detecting and categorizing brain cancers, particularly using clinical imaging modalities like magnetic resonance imaging (MRI). A thorough comparison of ML- and DL-based techniques used for brain tumor segmentation is covered in this work. Sophisticated DL architectures like CNN, U-Net, and transfer learning models are contrasted with traditional ML methods like SVM, RF, and KNN. Additionally covered are key preprocessing strategies, feature selection strategies, and segmentation strategies. Additionally, available datasets like BraTS and TCIA are used for comparison using common assessment measures including accuracy, precision, recall, and F1-score. In addition to discussing new developments like explainable AI and ensemble deep learning models, the survey is used to evaluate the paradigms' advantages and disadvantages as well as their suitability for use in clinical settings. The lessons learned are meant to direct future research toward more reliable, understandable, andclinically acceptable brain tumor diagnosis methods.

Key words: Brain tumor detection, Machine learning, Deep learning , Magnetic resonance imaging, medical image analysis.

I. Introduction

Brain tumors represent one of the most dangerous neurological conditions, frequently resulting in life-threatening complications and permanent mental disabilities. Timely and precise diagnosis is extremely critical for the optimization of patient outcomes and the choice of the adequate therapeutic approach. Conventional diagnostic methods, such the qualitative visual interpretation of Computed Tomography (CT) or Magnetic Resonance Imaging (MRI) scans by radiologists, are time-consuming, subjective, and prone to inter-observer variability. In light of this, the application of artificial intelligence (AI), more especially machine learning (ML) and deep learning (DL), to the medical imaging process has accelerated significantly.[18]
ML and DL algorithms have been greatly successful in task automation including image segmentation, feature extraction, tumor

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classification, and prognosis prediction. While DL techniques, such as Convolutional Neural Networks (CNNs), have revolutionized the field through end-to-end learning and automated feature extraction, traditional machine learning techniques rely on manually created features and explicit model-based classifiers.[17] The most significant approaches, datasets, and performance comparisons are highlighted in this paper's thorough analysis of machine learning and deep learning strategies for brain tumor detection, classification, and segmentation. The study aims to give a thorough grasp of current approaches, identify knowledge gaps, and recommend future directions for the advancement of AI-based brain tumor investigation.

II. Background

Brain tumors are abnormal growths of brain or covering tissues of the brain that may be benign or malignant. The most frequent ones are gliomas, meningiomas, and pituitary tumors, each of which is heterogeneous in shape, site, and aggressiveness. Accurate identification of tumor type is critical to clinical decision-making and treatment planning.

Medical imaging is the most essential component of diagnosing brain tumors. MRI is especially preferred because it has a high contrast resolution and can image soft tissues. MRI modalities like T1-weighted, T2-weighted, FLAIR, and contrast-enhanced images give detailed information regarding tumor structure and pathology. [21] Manual interpretation of these images is difficult owing to the complexity of tumor boundaries, heterogeneity, and tissue intensities superimposing each other.

Researchers increasingly turned to AI-based techniques to handle them. In earlier research, algorithms such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Decision Trees, and Random Forests were widely employed for tumor classification and detection. Usually derived from texture, form, or intensity features, these techniques incorporate carefully constructed features.[22] In contrast, deep learning algorithms—particularly CNNs and U-Net models—learn hierarchical representations of raw picture data directly, and they have significantly improved in accuracy and resilience in recent years.[23]

This review will concentrate on assessing and contrasting the efficacy of different ML and DL techniques applied to brain tumor analysis, providing recommendations on their relative merits, pitfalls, and clinical adoption prospects.

III. Traditional Machine Learning Approaches in Brain Tumor Analysis

Machine Learning (ML) has been a key contributor to the early efforts on the automation of brain tumor diagnosis from medical imaging data. Such methods are often a multi-stage pipeline involving image preprocessing, feature extraction, and classification with statistical or rule-based classifiers. Although Deep Learning has recently gained momentum, conventional ML methods are still providing stable and interpretable results, particularly where the dataset is compact or computational capability is limited.

A. Preprocessing and Feature Extraction

Proper preprocessing is required to improve the quality and consistency of input images. Skull stripping, noise elimination, normalization, and histogram equalization are some common methods. These processes aid in improving the transparency of tumor areas and eliminating unwanted information.

Feature extraction converts raw image data into a lower-dimensional space without losing significant features. Popular feature extraction methods in brain tumor analysis are:

• Gray-Level Co-occurrence Matrix (GLCM): Explores texture data by investigating spatial pixel value relationships.

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• Wavelet Transform: Breaks down images into frequency sub-bands for analysis at multiple resolutions.
• Principal Component Analysis (PCA): Conducted dimension reduction with the highest variance of the data preserved.
• Histogram of Oriented Gradients (HOG): Places focus on edge and shape information beneficial in the detection of tumors at boundaries.

B. Classification Algorithms

After feature extraction, different ML classifiers are employed for tumor classification and detection:
•Support Vector Machine (SVM): Commended for its capacity to identify the best hyperplanes in high-dimensional spaces. SVMs are efficient in binary classification and have proven to be very accurate in discriminating tumor and non-tumor tissues.
• K-Nearest Neighbors (KNN): A lightweight instance-based learning algorithm that makes a point a class based on proximity in feature space. Although computationally demanding at test, it performs well for well-separated classes.
• Random Forest (RF): An ensemble of decision trees that prevents overfitting and achieves high accuracy. RF models are insensitive to noise and are widely applied in multi-class tumor classification problems.
• Naïve Bayes (NB): Bayes' theorem-based probabilistic classifier. Though less accurate than other models, NB is computationally efficient and most appropriate for high-dimensional data.
• Decision Trees (DT): Interpretation-friendly and simple models that decide based on feature thresholds. DTs are frequently used as a baseline to compare more advanced classifiers against.

C. Applications in Literature

A number of studies have established the efficacy of ML algorithms in brain tumor detection. For example, SVMs with PCA and GLCM features have achieved over 90% classification accuracy on benchmark datasets such as Figshare and BraTS. Random Forest classifiers have also been used to detect gliomas and meningiomas with high sensitivity and specificity.

D. Advantages and Limitations

Classical ML methods are varied in having strengths such as interpretability, simplicity, and performance when working with small sets of data. They are highly reliant on feature extraction quality and domain expertise. They are also likely to be suboptimal when working with high-level structures from high-resolution images, and therefore they are limited to high-sophistication diagnostic applications.

IV. Deep Learning Techniques in Brain Tumor Analysis

Deep Learning (DL) has transformed the area of medical imaging with end-to-end solutions that can learn meaningful features from raw input without human involvement. In the detection and classification of brain tumors, DL models—specifically Convolutional Neural Networks (CNNs) have outperformed traditional machine learning approaches, particularly for use cases involving large-scale and complicated imaging data.
A. Convolutional Neural Networks (CNNs)
CNNs are now the standard architecture for brain tumor analysis because they are able to learn hierarchical spatial patterns. Most CNNs have many layers with convolutional, pooling, and fully connected layers being used to extract progressively abstract features from images. Some of the popular CNN architectures that have been used in brain tumor detection are:
•AlexNet and VGGNet: Early deep models with fine-tuning for tumor classification.

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•ResNet: Leverages residual connections to enable training of extremely deep networks with enhanced convergence and accuracy.
•DenseNet: Facilitates deeper feature reuse and tackles vanishing gradient.
Transfer learning has been employed by some studies by fine-tuning these pre-trained models for deployment on medical images with extremely accurate classification (often >95%) if used on test datasets like BraTS and Figshare.

B. Deep Learning for Segmentation
Accurate segmentation of brain tumors is critical for treatment planning and prognosis. Deep learning models like U-Net and its variants have been extensively employed for tumor segmentation tasks.

- U-Net: A symmetric encoder–decoder network with skip connections that captures fine-grained details. It has become the de facto standard for biomedical segmentation.
- 3D U-Net and V-Net: Designed for volumetric data, these models process 3D MRI scans for improved tumor boundary delineation.
- Attention U-Net: Incorporates attention mechanisms to focus on relevant tumor regions and suppress irrelevant background.

These models are evaluated using metrics such as the Dice Similarity Coefficient (DSC) and Intersection over Union (IoU), often achieving DSC scores above 0.85 in recent literature.

C. Ensemble and Hybrid Models
There have been some recent studies to couple DL and ML models to combine the strengths of both methods. For example, CNNs could be employed in feature extraction followed by conventional classifiers such as SVM or Random Forest for final classification. Ensemble techniques where several deep learning models are ensembled together have also been suggested to add robustness and accuracy.

V.ComparativeAnalysisofMachineLearning and Deep Learning Approaches
An exhaustive comparison of the conventional Machine Learning (ML) and Deep Learning (DL) methods uncovers glaring strengths and weaknesses for evaluating brain tumors. Whereas ML methods depend solely on hand-engineered features and knowledge in a particular domain, DL techniques automatically acquire hierarchical representations and therefore achieve state-of-the-art performance on tasks as difficult as segmentation and classification.

A. Performance Metrics and Evaluation
ML and DL methods are commonly qualitatively measured based on the following criteria:
• Accuracy: Number of instances classified correctly.
• Precision and Recall: Measures precision of positive predictions and capacity to recognize positive samples, respectively.
• F1-score: Harmonic mean of precision and recall.
• Dice Similarity Coefficient (DSC): Measures overlap between predicted and ground truth regions in segmentation.
• Area Under Curve (AUC): Measures classifier performance over thresholds.

B. Comparative Summary
Table I shows comparison of ML and DL methods based on some key parameters discussed in recent literature.

Table I: Comparison of ML and DL Approaches in Brain Tumor Analysis

Approach	Feature Extraction	Accuracy (%)	Interpretability	Dataset Dependency	Segmentation Support

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Approach	Feature Extraction	Accuracy (%)	Interpretability	Dataset Dependency	Segmentation Support
SVM + PCA + GLCM [1]	**Manual**	**~91%**	**High**	**Low–Medium**	**No**
Random Forest [2]	**Manual**	**~89%**	**Medium**	**Low**	**No**
CNN (Custom) [3]	**Automatic**	**~94%**	**Low**	**High**	**Partial**
ResNet50 (TL) [4]	**Automatic**	**~96%**	**Low**	**High**	**No**
U-Net (Segmentation) [5]	**Automatic**	**Dice ~0.87**	**Low**	**High**	**Yes**

C. Use Case Considerations

• ML techniques are ideally suited for small datasets or cases where interpretability is the key, such as early-stage research or aid diagnostic tools.

• DL methods excel in high-resolution imaging and end-to-end automation, making them ideal for large clinical datasets and real-time applications.

D. Integration Potential

More interest is being shown in hybrid methods that link ML and DL for better performance and interpretability. For example, application of CNNs for feature extraction followed by SVM for classification can provide a balance between accuracy and interpretability.

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VI. Datasets and Evaluation Metrics

The performance of machine learning and deep learning models in brain tumor analysis is heavily influenced by the quality and quantity of the datasets used. Standardized public datasets facilitate reproducibility and benchmarking of different models.

A. Commonly Used Datasets

For brain tumor identification and classification, various datasets available publicly have played important roles in driving studies. The datasets offer various imaging modalities, annotations, and clinical data, enabling the training and testing of machine learning (ML) and deep learning (DL)models

Dataset Name	Descr iption	Imaging Modalities	Appli cations	Refe rence
BraTS (Brain Tumor Segmentation Challenge)	Multi-institutional dataset with annotated MRI scans of glioma patients, including pixel-level tumor	T1, T1c, T2, FLAIR	Tumor segmentation, classification, survival prediction	[1]

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	segmentation masks.			
TCIA (The Cancer Imaging Archive)	Repository of medical imaging datasets, including brain tumor collections with clinical and genomic data.	MRI, CT	Classifi cation, radiomics, progre ssion studies	[2]
Figshare Brain MRI Dataset	Curated dataset for tumor classification tasks, comprising images categorized into glioma, meningioma, and pituitary tumors.	T1-weighted MRI	Tumor classificatio n	[3]
REMBRANDT	Dataset combining imaging and genomic data from brain tumor patients, supporting integrative analyses.	MRI	Genomic studies, classification	[4]
OASIS (Open Access Series of Imaging Studies)	Collection of MRI data aimed at studying normal aging and Alzheimer's disease, also utilized in brain tumor research.	T1-weighted MRI	Comparative studies, algorithm development	[5]

B. Decision Metrics

The following metrics are used to evaluate the performance of ML and DL based model for brain cancer analysis.:

- Accuracy (ACC): Indicates the proportion of cases that were accurately predicted. The formula for accuracy is TP + TN

TP+TN+FP+FN (1)

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Precision, Recall and F1-Score: These metrics are also useful for imbalanced datasets, they calculate the robustness of the ML model

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{F1-Score} = \frac{2\times \text{Precision x Recall}}{\text{Precision + Recall}} \quad (4)$$

Dice Similarity Coefficient (DSC): Specifically used for segmentation tasks to measure overlap between predicted and actual tumor regions.

$$DSC = \frac{2\times|A\cap B|}{|A|+|B|} \quad (5)$$

Under the ROC Curve (AUC): Evaluates the trade-off between sensitivity and specificity. These metrics allow objective comparison of model performance across different studies and datasets.

VI. Limitations and Future Prospectus

Despite significant progress in brain tumor identification and classification, several challenges continue to impede clinical translation. One of the primary limitations is the scarcity of large, well-annotated medical imaging datasets, which are essential for training and validating robust machine learning models. These are costly, time-consuming, and subject matter expert-reliant to obtain, tending to create class imbalance and poor generalizability. In addition, heterogeneity in data from differences in imaging protocols, models of scanners, and resolutions among institutions poses a major hindrance to model robustness. DL model interpretability is another major issue; the majority of top-performing networks are black boxes with low levels of transparency in decision-making, which decreases clinical confidence. High computational demands to train and run these models also limit their use, particularly in resource-limited environments. Furthermore, most ML/DL-based systems have not successfully transitioned from research systems to real-world clinical environments because of regulatory, validation, and workflow integration constraints. To overcome such constraints, future research can be dedicated to semi-supervised, self-supervised, and unsupervised learning methodologies decreasing the need for annotated data. Transfer learning and federated learning can improve model flexibility and privacy protection across institutions. The integration of multimodal data, i.e., MRI, histopathology images, and genomic information, has the potential to enhance tumor characterization and diagnosis accuracy. Moreover, the creation of lightweight and real-time models can facilitate broader adoption, especially in remote or resource-limited settings. Finally, the incorporation of explainable AI (XAI) platforms and ethical aspects, e.g., fairness and bias prevention, will be essential to create reliable and clinically meaningful AI systems.

VII. Conclusion

The use of machine learning (ML) and deep learning (DL) techniques for brain tumor categorization and detection has been examined in this research. Traditional machine learning techniques, such as Random Forests and Support Vector Machines (SVM), have shown promise in situations with small data sets and offer advantages in interpretability. On the other hand, DL models with automatic feature extraction and high segmentation accuracy, including Convolutional Neural Networks (CNNs) and U-Net-type systems, have proven to perform better when handling complex imaging data. The efficiency of diagnosis has also been increased by combining hybrid models that use both ML and DL techniques. Notwithstanding these developments, there are

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still many drawbacks, including the requirement for sizable annotated datasets, model interpretability, computing resource requirements, and clinical practice translation. Future studies will look at federated and semi-supervised learning techniques, build lightweight models that may be used in settings with limited resources, and use explainable AI techniques to model explainability. The successful integration of ML and DL techniques into clinical practice, which will ultimately improve patient outcomes and diagnostic precision in the treatment of brain tumors, depends on overcoming these obstacles.

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