A REVIEW: MACHINE LEARNING TECHNIQUES OF BRAIN TUMOR CLASSIFICATION AND SEGMENTATION

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Abstract Classifying brain tumors in magnetic resonance images (MRI) is a critical endeavor in medical image processing, given the challenging nature of automated tumor recognition. The variability and complexity in the location, size, shape, and texture of these lesions, coupled with the intensity similarities between brain lesions and normal tissues, pose significant hurdles. This study focuses on the importance of brain tumor detection and its challenges within the context of medical image processing. Presently, researchers have devised various interventions aimed at developing models for brain tumor classification to mitigate human involvement. However, there are limitations on time and cost for this task, as well as some other challenges that can identify tumor tissues. This study reviews many publications that classify brain tumors. Mostly employed supervised machine learning algorithms like support vector machine (SVM), random forest (RF), Gaussian Naive Bayes (GNB), k-Nearest Neighbors (K-NN), and k-means and some researchers employed convolutional neural network methods, transfer learning, deep learning, and ensemble learning. Every classification algorithm aims to provide an accurate and effective system, allowing for the fastest and most precise tumor detection possible. Usually, a pre-processing approach is employed to assess the system's accuracy; other techniques, such as the Gabor discrete wavelet transform (DWT), Local Binary Pattern (LBP), Gray Level Co-occurrence Matrix (GLCM), Principal Component Analysis (PCA), Scale-Invariant Feature Transform (SIFT) and the descriptor histogram of oriented gradients (HOG). In this study, we examine prior research on feature extraction techniques, discussing various classification methods and highlighting their respective advantages, providing statistical analysis on their performance.

Keywords: brain tumor, feature extraction, machine learning, deep learning.

1. Introduction

In today's society, health issues are more common than ever, and people's lifestyles are also getting more and more unhealthy [18]. In the human body, brain is the most complex organ; it is composed of nerve cells and tissues that regulate the most fundamental bodily functions, such as muscle movement, breathing, and the senses. Brain tumors are one of the most feared diseases in medical science because they are a type of tumor that affects the central nervous system [37]. According to 2016 cancer statistics provided by the World Health Organization (WHO), brain tumors are treated as the leading cause of cancer. The challenge of manually classifying brain tumor MR images with comparable structures or appearances is demanding and complicated. Classification of brain tumor

MR images with similar structures or appearances is a difficult and challenging task, to solve this issue, automated classification might be used to categorize MR images of brain tumors with the least amount of radiologists' involvement.

In recent years, medical image processing has emerged as a crucial tool for the early detection of brain cancer, attracting significant attention from researchers worldwide [54]. Efforts are focused on developing models to assist specialists in accurately predicting the presence of tumors [19]. Despite the challenges faced by developers, such as variations in image composition, dimensions, and pixel quality, artificial intelligence—particularly computer vision—plays a pivotal role in advancing the digitalization of medical diagnostics and enhancing active research in this field [41]. Deep learning (DL), a subset of machine learning, enables computers to discover data representations, anticipate future outcomes, and draw conclusions based on factual information. These techniques are considered among the most significant computational intelligence strategies and are widely applied in medical image classification [30]. However, without a pre-processing phase and effective feature extraction methods, many of these strategies fail to deliver their expected benefits [7]. Recently, machine learning (ML) and DL algorithms have gained prominence as powerful tools for medical image classification, with transformers and auto-encoders playing a critical role in addressing various challenges in the field.

Convolutional neural networks (CNNs) and vision transformers (ViTs), in capturing complex patterns and semantic details from medical images, thereby improving classification performance [3]. Autoencoders, commonly utilized in unsupervised learning, are instrumental in deriving meaningful representations from raw image data, aiding in feature identification and dimensionality reduction [2]. Moreover, Generative Adversarial Networks (GANs) offer the distinct ability to produce synthetic medical images, enhancing data augmentation and increasing the diversity of training datasets, which contributes to the creation of more robust classification models for medical imaging applications.

The accuracy of brain tumor data classification is influenced by various factors, including the type and complexity of the data, such as image composition, dimensions, and pixel quality. It also depends on the methods employed, the techniques used for feature extraction, and the parameters of the algorithms implemented in the approach [45].

The structure of this article is as follows. In Section 2 the search strategy is outlined. In Section 3 the existing literature is analysed in detail. Finally, in Section 4 the conclusions of the study and the proposed directions for future research are presented.

2. Search strategy

In our study numerous significant manuscripts employing various methods and techniques for brain tumor classification were studied. These articles were sourced from

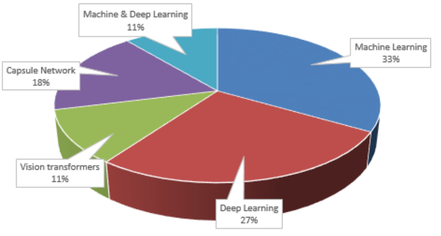

Fig. 1. The percentage of articles reviewed in this study.

platforms such as Google Scholar [58] and ScienceDirect [59]. Medical image classification approaches often leverage diverse machine learning algorithms and convolutional neural network architectures, including VGG, ResNet, AlexNet, and others. These methods incorporate distinct feature extraction techniques, such as descriptors, filters, and Gabor transforms. Additionally, advanced techniques like vision transformers and autoencoders have gained prominence, offering the ability to extract meaningful representations from image data and significantly improving image analysis and classification [52]. These approaches are complemented by standard preprocessing techniques, including resizing, normalization, data augmentation, and center cropping, which are commonly applied in the initial stages of image analysis workflows.

In this review, the referenced studies were systematically categorized according to the primary methodology employed: traditional Machine Learning, Deep Learning, Capsule Networks, and Vision Transformers. Approximately 33% of the cited articles focused on classical ML approaches, leveraging algorithms such as Support Vector Machines, Random Forests, and k-Nearest Neighbors. These methods often relied on handcrafted feature extraction techniques including Local Binary Patterns (LBP), Discrete Wavelet Transform (DWT), and Gray Level Co-occurrence Matrix (GLCM). Deep Learning-based studies accounted for around 27% of the references, with CNNs being the dominant architecture. These approaches demonstrated improved performance through automatic feature extraction and were frequently trained and evaluated on publicly available datasets such as BraTS [56], ISLES [55], and Figshare [57]. In addition to the individual contributions of Machine Learning (33%) and Deep Learning (27%) approaches, a notable 11% of the cited studies employed a hybrid ML & DL classification methodology, combining handcrafted features with deep feature representations to enhance classification accuracy. Capsule Networks were examined in roughly 18% of the cited work, offering robust spatial feature representation and enhanced interpretability, particularly in scenarios involving affine transformations. Vision Transformers, representing about 11% of the corpus, are an emerging trend, providing state-of-the-art performance by modeling global image context through self-attention mechanisms. Figure 1 illustrates the percentage of articles reviewed in this study.

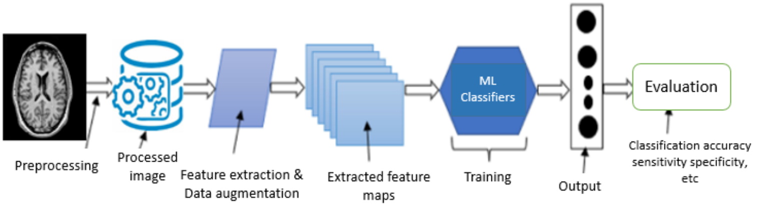

Fig. 2. Overview of the essential modules in a conventional ML-based brain tumor classification.

3. Analysis of the literature

The classification and segmentation of brain tumors remain an active area of research. Many researchers are exploring this topic, utilizing various techniques mentioned earlier to develop approaches with improved performance. The tables 1, 3, 4, 5, 6 below summarize the methods used in this field, including classification techniques, feature extraction methods, and the datasets employed.

3.1. Machine learning methods

Machine learning algorithms are among the most widely used methods for brain tumor classification, renowned for their effective detection capabilities. A key objective in many studies is to improve classification performance, which can be achieved through various methods and techniques applied at different stages. Enhancements may occur during dataset preprocessing, where traditional image processing techniques are implemented, or during the feature extraction phase, leveraging descriptors and neural network architectures. Furthermore, optimization during the classification phase, such as fine-tuning the algorithm's parameters, plays a crucial role in achieving superior results. Together, these efforts contribute significantly to improving the accuracy of classification outcomes. Figure 2 presents an overview of the essential modules in a conventional ML-based brain tumor classification.

Table 1 presents a comparison of studies that utilize different machine learning models, various feature extraction techniques, and diverse datasets to predict the classification accuracy of brain tumors.

Based on the findings presented in Tab. 1, it is evident that multiple factors play a role in enhancing the efficacy of brain tumor classification. Each approach employs specific methods and techniques tailored to its primary objective, encompassing various phases to achieve optimal results:

The standard data pre-processing stage is deemed crucial in the machine learning workflow, as it ensures that the data is appropriately configured for the application of

Tab. 1. Comparison of Machine Learning Models, Feature Extraction Methods, and Datasets for Brain Tumor Classification Accuracy.

Ref	Classification Method	Feature Extraction	Dataset	Accuracy
[27]	Machine Learning Methods Classifier	Crop, Resize, Augmentation, Transfer Learning	253 MRI, 3000 MRI, 3064 MRI	90%, 97%, 90%
[23]	LSTM	LBP, CNN	154 MRI	98%
[28]	Machine Learning	LBP	3064 MRI	95%
[33]	SVM, KNN, SRC, NSC, and the k-means	Wavelet, Statistical features	BraTS 2017	96%
[1]	Random Forest	Gray Level, LBP, HOG	BraTS 2013	93%
[12]	Random Forest Classifier	RGB to Gray, Resize, LBP, HOG, SFTA, GWF	BraTS 2012, BraTS 2014, BraTS 2015, BraTS 2017	90%, 89%, 94%, 91%
[38]	SVM Classifier, AC-CLS Segmentation	RGB to Graylevel Histogram Equalization, KMFCM	41 MRI	99%
[29]	LSTM	CNN, DWT	3064 MRI	98%
[14]	Support Vector Machine, K Nearest Neighbors, Neural Network, ELM	Resize, Watershed segmentation, morphological process, Wavelet	16 MRI	96%
[21]	Decision Tree, Multi-Layer Perceptron	Sigma Filter, Adaptive threshold, Region Detection, Binary Object Feature	174 MRI	95%, 91%
[11]	Machine Learning Methods Classifier	Weiner filter, Potential Field clustering, threshold, morphological dilation, LBP, GWT	86 MRI, BraTS 2013, BraTS 2015	93%, 93%, 97%
[42]	MLP Naïve bayes	RGB to Grey (Binarization), Median Filter (Noise Remove), edge detection, watershed, GLCM	212 MRI	98%, 91%
[51]	Machine Learning, Ensemble Learning	Crop, Resize, Augmentation, DWT, HOG	253 MRI	92%
[43]	Support vector machine	DTI analysis, Perfusion analysis, segmentation, normalization	141 MRI	97%
[39]	Support vector machine	Contrast Stretching, Augmentation, Transfer learning AlexNet, GoogLeNet, VggNet	3064 MRI	98%

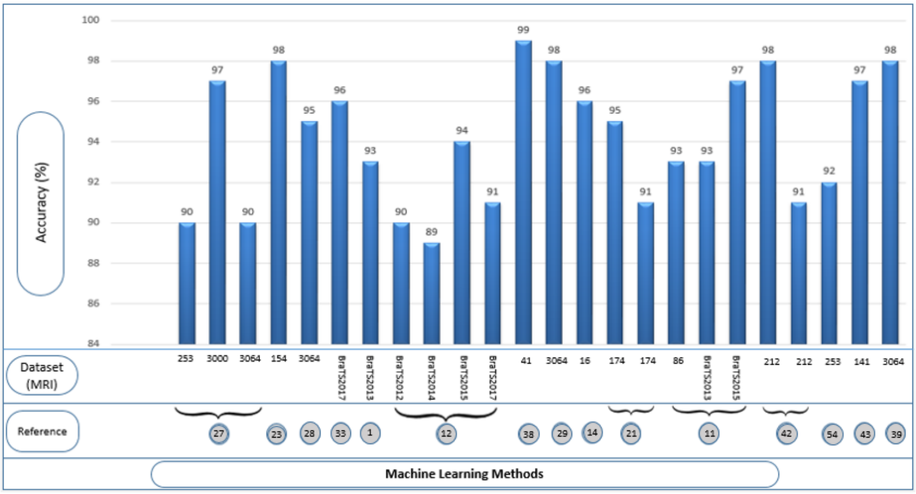

Fig. 3. The classification accuracy reported in each brain tumor study, based on machine learning algorithms and their respective datasets. Labels given in the row "Reference" are related to literature references according to Tab. 2, p. 37.

learning algorithms, thereby enhancing the quality, convergence, and performance of resultant models. This phase encompasses techniques such as data cleaning, normalization, scaling, and augmentation, all of which are recommended for thorough examination.

The feature extraction phase plays a pivotal role in enhancing data representation and reducing dimensionality for improved interpretability and comprehension. Various techniques, including CNN layers, LBP, DWT, HOG, GLCM, dilation, and filters, are commonly employed in this phase, each serving a specific purpose. Making the right choice of technique can significantly enhance classification accuracy. In the final phase, known as the classification or decision-making phase, the selection of parameters for the classification algorithm significantly impacts the effectiveness of the approach.

Figure 3 illustrates the highest accuracy rates achieved for brain tumor classification across different datasets. These accuracies were obtained through the application of various machine learning methods, highlighting the effectiveness of the employed classification techniques. Notably, the preprocessing and feature extraction methods played a crucial role in enhancing the model performance. By refining the input data, reducing noise, and selecting the most relevant features, these techniques contributed significantly to the high accuracy observed in the figure. This evaluation underscores the importance of carefully designing preprocessing pipelines and feature extraction strategies to optimize classification performance in brain tumor diagnosis.

Traditional machine learning algorithms, while effective in numerous classification

Tab. 2. Relations of labels given in Figs. 3, 5, 6, 8, 10 in the row 'References' to the literature references denoted here as 'Ref.'.

Label	Ref.	Label	Ref.	Label	Ref.	Label	Ref.	Label	Ref.
1	[1]	4	[4]	5	[5]	6	[6]	7	[7]
8	[8]	9	[9]	10	[10]	11	[11]	12	[12]
13	[13]	14	[14]	15	[15]	16	[16]	17	[17]
20	[20]	21	[21]	23	[23]	24	[24]	25	[25]
26	[26]	27	[27]	28	[28]	29	[29]	31	[31]
32	[32]	33	[33]	34	[34]	36	[36]	38	[38]
39	[39]	40	[40]	42	[42]	43	[43]	44	[44]
46	[46]	47	[47]	48	[18]	49	[48]	50	[49]
52	[50]	54	[51]	56	[53]				

tasks, exhibit several limitations when applied to complex medical imaging scenarios. One of the primary challenges lies in their reliance on handcrafted feature extraction, which often demands significant domain expertise and may fail to capture the full intricacies of high-dimensional medical data such as MRI scans. This manual process can lead to suboptimal performance, particularly in cases where subtle spatial patterns are critical for accurate tumor classification or segmentation. Furthermore, traditional ML models typically struggle with generalization when applied to diverse datasets or varying imaging conditions. To address these shortcomings, deep learning techniques—especially convolutional neural networks—have emerged as a powerful alternative. These models are capable of automatically learning hierarchical features directly from raw data, reducing the dependency on manual intervention and enhancing model robustness. By capturing both low-level and high-level features through stacked layers, deep learning architectures offer improved performance and scalability, making them more suitable for complex brain tumor analysis tasks. As a result, the shift from traditional ML to DL represents a significant advancement in the development of more accurate and automated diagnostic tools.

3.2. Deep learning methods

Convolutional Neural Networks are a type of multi-layer feedforward artificial neural network, initially inspired by the visual cortex [22]. CNNs play a pivotal role in deep learning and have emerged as one of the most commonly used architectures in recent

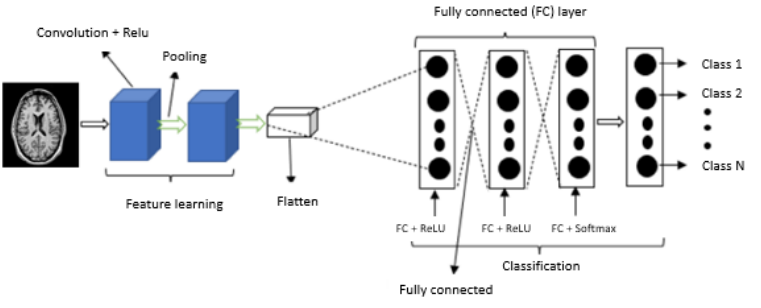

Fig. 4. Illustration showing the fundamental layers of a Convolutional Neural Network.

years, particularly for image recognition tasks. They excel in performing complex operations through convolution filters, which enable effective feature extraction. The convolutional layers in CNNs progressively learn intricate visual patterns from raw input data by applying filters to detect features such as edges, textures, and patterns in images. This hierarchical representation of data not only facilitates a deeper understanding of the inherent structures within the data but also significantly enhances classification performance. The initial layer in a Convolutional Neural Network serves to introduce the input image into the model, initiating the processing sequence through subsequent layers. As the data progresses, convolutional operations, pooling layers, and activation functions work collaboratively to extract meaningful and abstract features from the input. These features are then passed to one or more fully connected layers, which play a crucial role in tasks such as classification, segmentation, or detection of objects within the image. Ultimately, the final output is produced by the output layer, which delivers the network's prediction or decision. A typical CNN structure is depicted in Figure 4.

Table 3 presents a comparison of studies that utilize different deep learning architectures, various feature extraction techniques, and diverse datasets to predict the classification accuracy of brain tumors.

The findings in the table underscore critical factors contributing to the optimization of brain tumor classification methods, with each approach utilizing specific methods and techniques across various phases:

- Data Preprocessing: This phase is vital for preparing data for learning algorithms, which enhances model quality, convergence, and overall performance. Techniques such as data cleaning, normalization, scaling, and augmentation play an essential role in ensuring the data is well-suited for analysis.
- Feature Extraction: A key step in improving data representation and reducing dimensionality, feature extraction enhances interpretability and contributes significantly to classification accuracy. Methods like CNNs layers, local binary patterns (LBP), discrete wavelet transforms (DWT), histograms of oriented gradients (HOG), gray-level

Tab. 3. Comparison of Deep Learning Architectures, Feature Extraction Methods, and Datasets for Brain Tumor Classification Accuracy.

Ref.	Classification Method	Feature Extraction	Dataset	Accuracy
[31]	CNN Classifier	RGB to Grayscale, Edge detection, Morphological operation, watershed	500 MRI	72%
[40]	CNN Classifier	histogram equalization technique, Gaussian filter	3064 MRI	93%
[46]	CNN Classifier	Resize, Augmentation, Grayscale, regularization techniques	3064 MRI, 516 MRI	96%, 98%
[32]	DNN	Fuzzy C-means, DWT, PCA	66 MRI	97%
[16]	CNN Classifier	Resize, Augmentation	3064 MRI	97%
[44]	CNN Classifier	MidResBlock	3064 MRI	96%
[10]	DNN Classifier	Resize, Crop Lesion, Uncropped Lesion, segment Lesion	3064 MRI	98%
[47]	CNN Classifier	MidResBlock	3064 MRI	94%
[13]	DNN	Resize, CNN, Segmentation	BraTS 2012, BraTS 2013, BraTS 2014, BraTS 2015, ISLES 2016, ISLES 2017	98%, 99%, 100%, 93%, 95%, 98%
[48]	Ensemble of ViTs	optimization of transformer parameters	3064 MRI	98.7%
[9]	Hybrid transformer enhanced convolutional neural network (TECNN)	CNN, Attention mechanism	BraTS 2018, Figshare datasets	96.75%, 99.1%

co-occurrence matrices (GLCM), dilation, and various filters provide specialized benefits in this regard.

- Classification: The selection of parameters in this phase has a profound impact on the effectiveness of the approach. Careful and informed parameter choices are essential to maximize performance and achieve optimal results.

Figure 5 presents a graphical representation of the highest accuracy rates achieved for brain tumor classification across different datasets using deep learning methods, particularly Convolutional Neural Networks. The remarkable performance observed can be attributed to the effectiveness of CNNs in automatically extracting relevant features

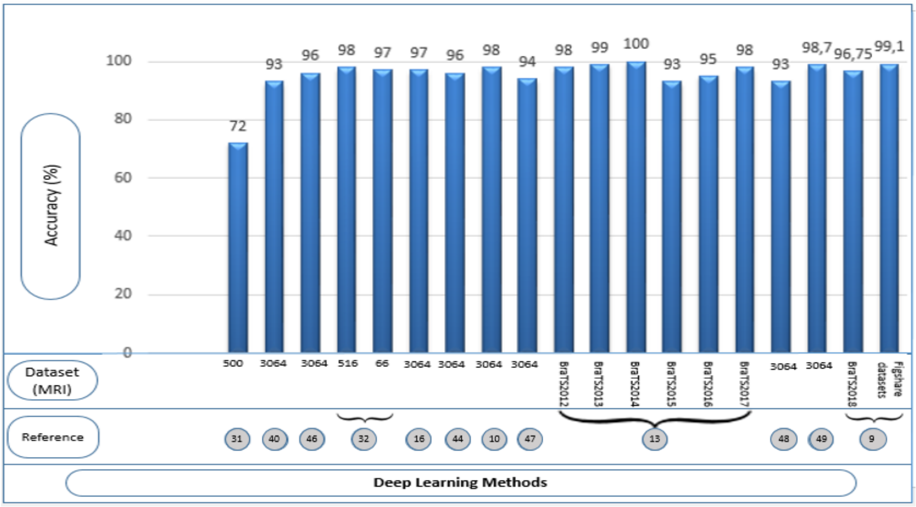

Fig. 5. The classification performance achieved in various brain tumor studies utilizing deep learning techniques across different datasets. Labels given in the row "Reference" are related to literature references according to Tab. 2, p. 37.

from medical images. Furthermore, preprocessing techniques such as image normalization, augmentation, and noise reduction have played a key role in enhancing the quality of input data, ultimately improving model accuracy. The combination of well-structured preprocessing pipelines and robust feature extraction capabilities of CNNs has significantly contributed to achieving high classification performance, demonstrating the potential of deep learning in brain tumor diagnosis.

Despite the considerable advancements brought by deep learning in medical image analysis, several limitations continue to hinder its full potential in clinical applications. Deep learning models, especially convolutional neural networks, demand extensive computational power and access to large, well-annotated datasets to achieve high performance. In practice, such datasets are often scarce, particularly in specialized medical domains like brain tumor diagnosis. Furthermore, these models are prone to overfitting, especially when trained on limited data, and their "black-box" nature makes their decision processes difficult to interpret. Additionally, deep learning algorithms may struggle to generalize effectively when applied across different clinical settings or imaging devices. To address these issues, recent research has explored hybrid approaches that integrate the strengths of both traditional machine learning and deep learning techniques. These combined frameworks often use deep learning for automated feature extraction, followed by classical ML algorithms—such as SVM or Random Forest—for final classification. This strategy not only reduces dependency on large labeled datasets but also enhances model interpretability and robustness. By leveraging the complementary advantages of both paradigms, these integrated systems aim to improve diagnostic accuracy and reliability in complex imaging tasks.

3.3. ML and CNN

Recently, numerous approaches have employed convolutional neural networks in combination with machine learning algorithms to enhance classification performance. This research focuses on integrating CNN techniques with various machine learning algorithms to optimize performance in image classification tasks. By harnessing the feature extraction capabilities of CNNs alongside the adaptability of machine learning algorithms for classification, these approaches aim to achieve significant improvements in classification accuracy. This integration contributes to advancements in computer vision and pattern recognition, paving the way for more effective solutions in the field. Table 4 presents a comparison of studies that utilize different machine learning models and deep learning architectures, various feature extraction techniques, and diverse datasets to predict the classification accuracy of brain tumors.

Based on the results presented in Tab. 4, we observe the significant advancements in CNN techniques and machine learning algorithms for extracting intricate features from complex datasets, particularly in the field of image classification. By harnessing the

Tab. 4. Comparison of machine learning models and deep learning architectures, Feature Extraction Methods, and Datasets for Brain Tumor Classification Accuracy.

Ref.	Classification Method	Feature Extraction	Dataset	Accuracy
[35]	SVM, DNN	Fuzzy C-Means (FCM), CNN	BraTS 2015	97%
[20]	SVM, KNN, transfer learned, deep network	GoogLeNet, CNN	3064 MRI	97%, 98%, 92%
[34]	artificial neural network, Parzen window, k-Nearest Neighbors	Wavelets, PCA	166 MRI	98%, 99%, 99%
[53]	Machine Learning Methods Classifier, VGG16	Resize, Augmentation, Crop, Transfer Lerning	253 MRI	88%, 98%
[17]	SVM, Decision Tree, Random Forest, CNN, ResNet 50, AlexNet, Google Lenet, hybrid DCNN-LUNET	Resize, Laplace Gaussian (LOG) filtering and contrast-limited adaptive histogram smoothing, VGG-16, ROI Segmentation, FCM-GMM	260 MRI	97%, 96%, 97%, 98.82%

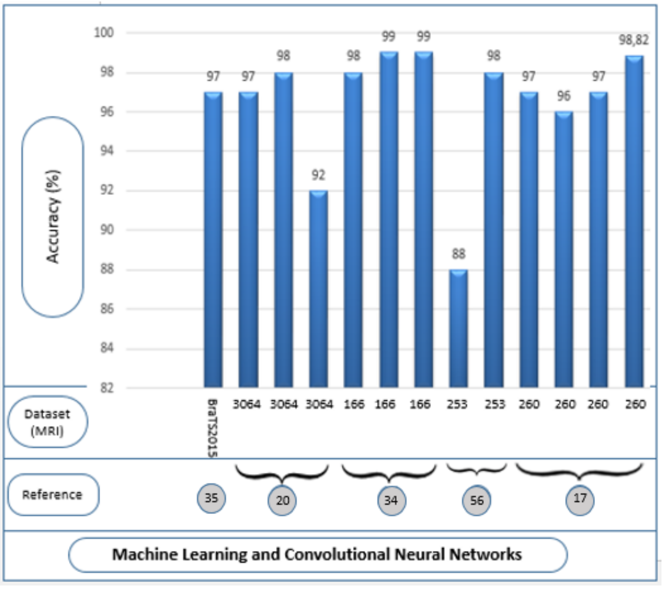

Fig. 6. The classification outcomes reported in several brain tumor studies that employed Machine and Deep Learning approaches on diverse datasets. Labels given in the row "Reference" are related to literature references according to Tab. 2, p. 37.

hierarchical feature extraction capabilities of CNNs alongside the discriminative power of machine learning algorithms, these approaches strive to substantially enhance classification performance. This integration aims to achieve higher accuracy and robustness in classifying diverse image datasets, thereby contributing to progress in computer vision and pattern recognition research.

Figure 6 illustrates the highest accuracy rates achieved for brain tumor classification across various datasets using both traditional machine learning techniques and Convolutional Neural Networks. The superior performance is largely influenced by the effectiveness of feature extraction methods, which play a crucial role in distinguishing tumor types. Preprocessing steps, including contrast enhancement, noise reduction, and data augmentation, further refine the input images, ensuring better model generalization. The combination of handcrafted feature extraction in machine learning and automatic feature learning in CNNs has led to significant improvements in classification accuracy, highlighting the importance of data quality and of the preprocessing steps in achieving optimal results.

Traditional machine learning techniques face notable limitations, particularly in the context of complex medical imaging tasks such as brain tumor classification. These methods often depend on handcrafted feature extraction, which requires substantial domain knowledge and may overlook critical spatial or contextual information embedded in the images. Although deep learning has emerged as a powerful alternative—capable of learning hierarchical features directly from raw data—it also presents significant challenges. These include the necessity for large annotated datasets, high computational requirements, risk of overfitting, limited transparency in decision-making, and reduced adaptability across heterogeneous clinical settings. In light of these issues, Capsule Networks have been proposed as a promising new approach. Unlike conventional CNNs, Capsule Networks are designed to preserve spatial hierarchies and relationships between features, making them more robust to affine transformations and better suited for modeling complex structures in medical images. Moreover, their architecture allows for enhanced interpretability and potentially better generalization from smaller datasets, offering a compelling direction for overcoming some of the critical shortcomings observed in both traditional ML and standard deep learning models.

3.4. Capsule network architectures

While convolutional neural networks have been extensively utilized for feature extraction in image processing tasks, they exhibit limitations in capturing spatial relationships among features. Capsule Networks address this limitation by preserving the spatial hierarchy of features more effectively. CapsNets introduce the concept of capsules, which encapsulate spatial information more efficiently than traditional CNNs. Furthermore, CapsNets offer significant advantages, including improved generalization, robustness to affine transformations, and enhanced interpretability. These qualities make them a compelling alternative for tasks requiring accurate spatial feature extraction and classification in medical imaging. The table below provides a detailed overview of various methodologies that employ capsule networks for brain tumor classification. Figure 7 illustrates the standard pipeline employed in brain tumor segmentation approaches utilizing Capsule Networks (CapsNet).

Table 5 presents a comparison of studies that utilize capsules networks architectures, various feature extraction techniques, and diverse datasets to predict the classification accuracy of brain tumors.

Currently, much research in classification highlights the limitations of traditional CNNs in effectively extracting spatial features, largely due to their reliance on pooling operations, which can result in the loss of critical spatial information. To overcome these challenges, recent studies have explored the use of capsule networks as a promising alternative. Capsule networks are specifically designed to capture hierarchical spatial relationships within images more effectively than CNNs, potentially improving feature extraction and classification accuracy. Additionally, capsule networks provide several advantages, including better handling of spatial hierarchies, increased robustness

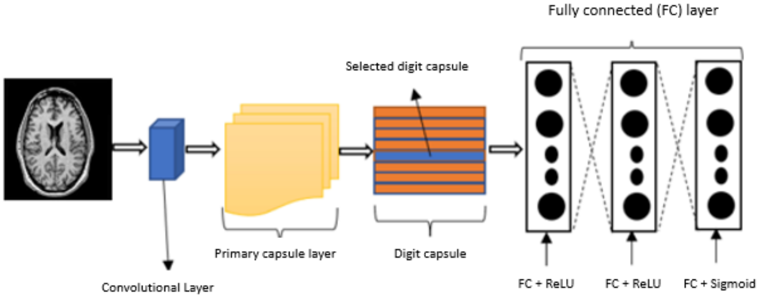

Fig. 7. Illustration of a typical segmentation workflow leveraging Capsule Networks.

Tab. 5. Comparison of capsules networks architectures, Feature Extraction Methods, and Datasets for Brain Tumor Classification Accuracy.

Ref.	Feature Extraction	Dataset	Accuracy
[6]	Hyperparameter optimization	3064 MRI	90%
[7]	T-distributed Stochastic Neighbor Embedding (TSNE)	3064 MRI	86%
[8]	Boosting approach	3064 MRI	92%
[49]	Rotation and patch extraction	3064 MRI	94%
[4]	activation function	3264 MRI	96.7%
[5]	CapsNet, dilation convolution	3064 MRI	95.54%
[15]	SegCaps–Capsule network, brain tumor segmentation	BraTS 2020	87.96%

to affine transformations, and enhanced interpretability of learned features. This innovative approach addresses the shortcomings of CNNs in spatial feature extraction, offering significant advancements in image classification for medical applications.

The strong performance of these models can be attributed to their ability to capture spatial hierarchies and maintain spatial relationships between features, unlike traditional CNNs. The effectiveness of the model is further enhanced by preprocessing techniques such as normalization, noise reduction, and data augmentation, which improve the quality of input data. Additionally, robust feature extraction methods contribute to the model's capacity to distinguish complex patterns within brain tumor images, ultimately leading to superior classification accuracy. The chart in Fig. 8 illustrates the classification outcomes reported in several brain tumor studies that employed Capsule Network approaches on diverse datasets.

While Capsule Networks have demonstrated significant potential in preserving spatial hierarchies and improving robustness to affine transformations, they still face several practical limitations that hinder their widespread adoption in medical imaging tasks.

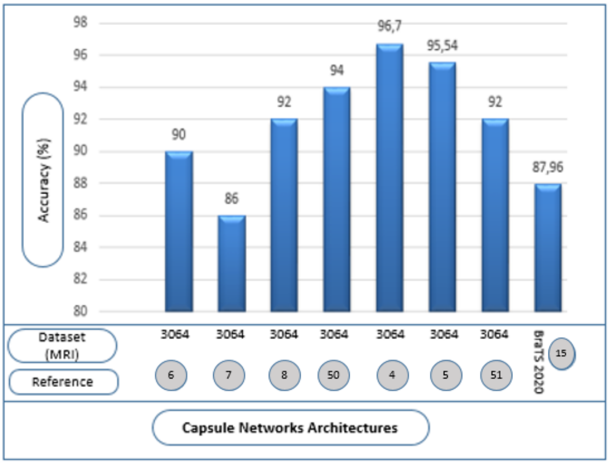

Fig. 8. The classification performance achieved in various brain tumor studies utilizing capsule networks techniques across different datasets. Labels given in the row "Reference" are related to literature references according to Tab. 2, p. 37.

One of the main challenges lies in their computational inefficiency; the dynamic routing mechanism, which is central to Capsule Networks, is resource-intensive and leads to slower training and inference times. Additionally, these networks are relatively sensitive to hyperparameter tuning and lack standardized architectures, making their implementation and optimization more complex compared to traditional deep learning models. In response to these shortcomings, Vision Transformers have emerged as a compelling alternative. Unlike Capsule Networks, ViTs leverage self-attention mechanisms to model global dependencies within an image, allowing for more efficient capture of contextual information across the entire visual field. Moreover, Vision Transformers demonstrate greater scalability and adaptability, showing strong performance even when trained on relatively limited data through techniques such as transfer learning and data augmentation. As research in this area progresses, ViTs are increasingly being considered as a powerful tool for medical image classification and segmentation, potentially overcoming the architectural and computational limitations associated with Capsule Networks.

3.5. Vision Transformers

Recent advances in image classification have drawn attention to the inherent limitations of conventional Convolutional Neural Networks, particularly in capturing long-range dependencies and global contextual information within medical images. These limitations stem mainly from the localized nature of convolution operations and the use of pooling layers, which can lead to the loss of important spatial relationships. To address these

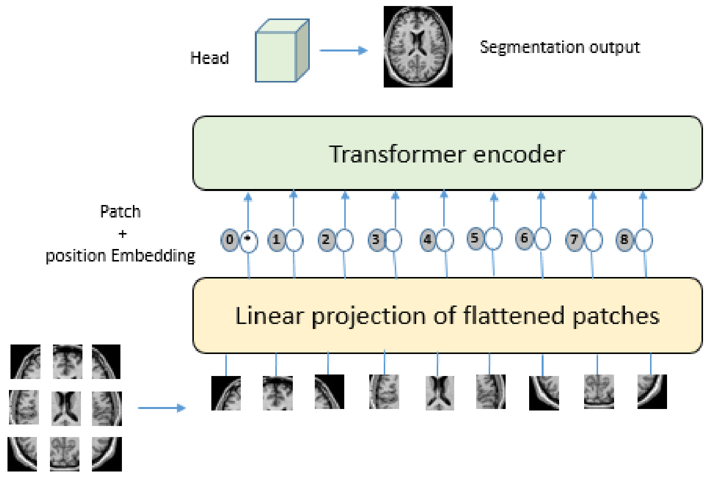

Fig. 9. Overview of the Vision Transformers model.

issues, researchers have increasingly explored Vision Transformers as a powerful alternative. Unlike CNNs, Vision Transformers leverage self-attention mechanisms to model global interactions across the entire image, allowing for more comprehensive and context-aware feature representation. This enables ViTs to retain critical spatial and semantic details, enhancing classification performance. Furthermore, ViTs offer advantages such as scalability, better generalization in complex datasets, and improved interpretability due to their attention maps, which highlight key regions influencing decision-making. This modern architecture represents a promising direction for improving image classification in brain tumor analysis and other medical imaging tasks.

The high performance of these models can be credited to their ability to analyze images holistically, maintaining spatial coherence while focusing on the most informative regions through self-attention. Unlike CNNs, which process image patches locally, ViTs treat the entire image as a sequence of patches, enabling the network to recognize complex global patterns that are essential in medical image analysis. This performance is further strengthened by preprocessing strategies such as image normalization, denoising, and data augmentation, which enhance input consistency and variability. Additionally, the integration of advanced feature extraction pipelines allows the model to effectively distinguish between subtle differences in tumor structures, leading to highly accurate and reliable classification outcomes. These capabilities make Vision Transformers a compelling choice for future developments in AI-assisted medical diagnostics. Figure 9 illustrates the standard pipeline employed in brain tumor segmentation approaches utilizing vision transformers.

Table 6 presents a comparison of studies that utilize vision transformers architectures, various feature extraction techniques, and diverse datasets to predict the classification accuracy of brain tumors.

Based on the analysis shown in Tab. 6, it becomes clear that various components contribute significantly to improving the performance of brain tumor classification systems. Each method integrates specific techniques aligned with its core objective, progressing through several essential stages to achieve optimal accuracy. The data preprocessing phase remains fundamental in Vision Transformer-based workflows, as it prepares the input for optimal attention-based modeling. Techniques such as normalization, image denoising, patch embedding, resizing, and data augmentation are critical in ensuring consistency, reducing artifacts, and enhancing generalization. These operations help the model interpret input images more effectively during training and inference.

The feature representation and encoding stage is particularly crucial in Vision Transformers. Instead of relying on handcrafted features or convolutional layers, ViTs divide images into fixed-size patches and transform them into sequences of embeddings, which are processed through self-attention layers. This enables the model to capture both local and global dependencies across the entire image, significantly enriching the representation of complex patterns in brain tumor regions. Additionally, position embeddings are integrated to retain spatial information, further improving interpretability.

Finally, during the classification stage, the transformer encoder's output is used to make predictions through fully connected layers. The effectiveness of this stage is influenced by the architecture's depth, the number of attention heads, and the choice of loss functions and optimization strategies. The Figure 10 highlights the top classification accuracies achieved across multiple datasets using Vision Transformer-based models. These impressive results are largely attributed to the robust preprocessing procedures and the ViTs' superior ability to model long-range spatial relationships. The evaluation reaffirms the importance of designing effective preprocessing workflows and utilizing advanced attention mechanisms to optimize classification performance in brain tumor diagnostics.

Tab. 6. Comparison of Vision Transformers model, Feature Extraction Methods, and Datasets for Brain Tumor Classification Accuracy.

Reference	Feature Extraction	Dataset	Accuracy
[50]	Transformers and 3D CNN	BraTS 2019, BraTS 2020	90.09%
[24]	Swin transformers and CNN	BraTS 2021	93.3%
[25]	Transformers and CNN	MSD dataset	78.9%
[26]	Transformers and 3D CNN	BraTS 2021	90.8%
[36]	Transformers and 3D CNN "U-Net shaped encoder-decoder"	BraTS 2021	91.2%

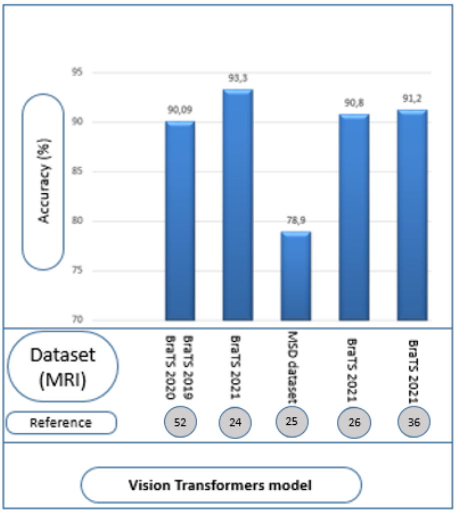

Fig. 10. The classification accuracy of each study on brain tumors, based on vision transformers and the corresponding datasets used. Labels given in the row "Reference" are related to literature references according to Tab. 2, p. 37.

The figure below presents the classification results obtained from multiple brain tumor studies that adopted Vision Transformer-based methods across various datasets.

Although Vision Transformers have gained traction for their ability to model long-range dependencies and capture global image context more effectively than traditional convolutional approaches, they are not without limitations. One of the primary challenges associated with ViTs is their need for extensive training data to perform optimally, which can be a significant constraint in the medical imaging field where labeled datasets are often limited. Additionally, their architecture tends to be computationally demanding, both in terms of memory usage and training time, which can limit their accessibility in resource-constrained clinical environments. ViTs also exhibit sensitivity to hyperparameter selection and are often less interpretable compared to some traditional machine learning models. These constraints have sparked a wave of innovation among researchers who are actively exploring novel hybrid models, architectural optimizations, and lightweight transformer variants tailored to medical contexts. The current trend involves designing more efficient classification algorithms that combine the strengths of ViTs with other paradigms, such as convolutional modules or attention-enhanced ML models, to achieve better accuracy, generalizability, and scalability. This competitive research environment is fostering the development of next-generation models that aim to balance performance, efficiency, and interpretability for robust brain tumor classification and other critical diagnostic tasks.

3.6. Discussion

In conclusion, the classification of brain tumors using Machine Learning, Deep Learning, Capsule Network architectures, and Vision Transformers model has demonstrated significant advancements in accuracy and robustness. DL approaches, particularly Convolutional Neural Networks, have surpassed ML techniques by automatically learning hierarchical features, improving generalization. More recently, Capsule Networks have further enhanced classification performance by preserving spatial relationships between features, addressing limitations of CNNs in detecting complex structures. The effectiveness of these models is strongly influenced by preprocessing techniques such as normalization, noise reduction, and data augmentation, which enhance input quality. Additionally, feature extraction methods play a crucial role in identifying relevant tumor characteristics, leading to improved classification accuracy. The integration of advanced architectures with optimized preprocessing and feature extraction strategies paves the way for more reliable and precise brain tumor diagnosis, contributing to enhanced decision-making in medical imaging.

A critical challenge in deploying ML, DL, Capsnet and Vit models for brain tumor analysis lies in their limited ability to generalize across diverse clinical settings. Variations in MRI acquisition protocols, scanner types, and patient populations often lead to distributional shifts that can significantly impact model performance. Models trained on a specific dataset may not perform reliably when applied to external data due to differences in resolution, contrast, noise levels, and anatomical variability. Addressing this issue requires the integration of domain adaptation techniques, robust data augmentation, and cross-institutional validation to ensure that AI models remain accurate, consistent, and clinically applicable across a wide range of imaging environments.

4. Conclusion and future scope

In this review, we provided an in-depth examination of recent advances in brain tumor classification and segmentation, focusing on notable research studies that implement a variety of machine learning, deep learning, Capsule Networks, and Vision Transformers techniques. These studies have contributed significantly to the improvement of classification performance through enhanced feature extraction, preprocessing, and the careful selection of classification algorithms. The analysis underscores the importance of each stage in the diagnostic pipeline—from data preparation through normalization and augmentation, to robust feature extraction using methods like CNNs, Gabor filters, DWT, LBP, and GLCM, and finally to accurate classification through optimized models.

While the reviewed models demonstrate impressive performance, this study also acknowledges key limitations that remain a challenge in clinical applications. For instance, traditional ML approaches rely heavily on handcrafted features, which often limit their performance in complex imaging contexts. DL models, although more effective in learning features automatically, face challenges such as high computational demands, the need for large annotated datasets, interpretability issues, and limited generalizability across diverse clinical environments.

To address these challenges, emerging research is exploring hybrid models that combine ML and DL to leverage the strengths of both paradigms. Additionally, recent developments in Capsule Networks and Vision Transformers present promising alternatives by offering improved spatial awareness and better feature representation. However, these models also face issues such as high training complexity, stability concerns, and a lack of standardized benchmarks.

This area is in the urgent need for models that generalize well across different MRI acquisition protocols and scanner types, as well as the development of computationally efficient architectures suitable for real-time clinical deployment. Furthermore, advancing techniques such as transfer learning, semi-supervised learning, and explainable AI are critical to overcoming current limitations.

Finally, while our review primarily focuses on brain tumor classification, the discussed techniques have broader applications, including the diagnosis of other neurological diseases such as Alzheimer's and Parkinson's. As the field evolves, our future research aims to develop versatile, interpretable, and clinically adaptable AI tools to support early and accurate diagnosis across a wide range of brain pathologies.

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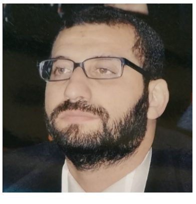

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