**A Comprehensive Survey on Brain Tumor Segmentation and Classification using Deep Learning Techniques**

**Abstract:**

Brain tumor classification is a pivotal task in the realm of medical image analysis, crucial for accurate diagnosis and treatment planning. The integration of deep learning methodologies has emerged as a transformative approach, demonstrating substantial improvements in classification accuracy and efficiency. This survey paper provides an in-depth exploration of recent advances in the application of deep learning techniques for brain tumor classification, offering a comprehensive overview of methodologies, architectures, datasets, and challenges. The motivation for this survey stems from the limitations of traditional methods in handling the complexity and variability of brain tumor characteristics. Deep learning, with its capacity to automatically learn hierarchical features from raw data, has shown great promise in addressing these challenges. By delving into the intricacies of medical imaging modalities such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT), this survey aims to elucidate the specific nuances of applying deep learning to different imaging technologies. A significant portion of the survey is dedicated to exploring various deep learning architectures, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transfer Learning. Each architecture's strengths and weaknesses are scrutinized in the context of brain tumor classification, providing a nuanced understanding of their applicability. In conclusion, this survey paper aims to consolidate the current state of knowledge in the field of brain tumor classification using deep learning. By synthesizing key findings and highlighting future directions, it serves as a valuable resource for researchers, practitioners, and healthcare professionals seeking to leverage the potential of deep learning in enhancing brain tumor diagnosis and treatment planning.

**Keywords:**

Brain Tumor detection, Deep learning, Magnetic Resonance Imaging, Computed Tomography, Convolutional Neural Networks, Recurrent Neural Networks and Transfer Learning.

**1. Introduction**

**1.1 Background:**

Brain tumors represent a formidable global health challenge, with an estimated annual incidence of over 500,000 cases worldwide, according to the World Health Organization (WHO). These tumors, characterized by abnormal growth within the brain or the surrounding tissues, exhibit a diverse range of morphological and histological features, making their classification and subsequent treatment a complex and critical endeavor. Traditional methods of brain tumor classification, reliant on manual feature extraction and rule-based systems, often fall short in accurately capturing the intricacies of these tumors. The impact of brain tumors on individuals and society at large is profound. Globally, brain and nervous system cancers are ranked as the 19th leading cause of cancer-related deaths, accounting for approximately 2.2% of all cancer-related mortality. Moreover, the burden extends beyond mortality rates, as survivors often face long-term neurological consequences and diminished quality of life. The urgency to address this impact has fueled the exploration of advanced computational approaches, particularly deep learning, to improve the accuracy of classification and enhance treatment outcomes.

**1.2 Motivation:**

The motivation to explore deep learning in brain tumor classification is deeply rooted in the unmet clinical needs, the human impact of brain tumors, and the compelling potential of advanced computational techniques to revolutionize diagnostic paradigms.

* Clinical Imperatives: The complexity and heterogeneity of brain tumors pose substantial challenges for accurate and timely diagnosis. Traditional methods, often reliant on manual assessment and predefined rules, struggle to capture the nuanced variations in tumor characteristics. This inherent complexity motivates the exploration of deep learning, as it has demonstrated unparalleled capabilities in automatically learning intricate patterns and representations directly from raw imaging data. The urgency to bridge diagnostic gaps and improve the precision of brain tumor classification is a driving force behind the adoption of these cutting-edge technologies.
* Human Impact: Beyond the statistics and economic burdens, the human impact of brain tumors is profound. Individuals facing a potential diagnosis grapple not only with the physical manifestations of the disease but also with the emotional and psychological toll. The uncertainty surrounding diagnosis and treatment decisions adds an additional layer of stress. Motivated by a commitment to alleviate this burden, the integration of deep learning in brain tumor classification seeks to provide quicker and more accurate diagnoses. Improved classification outcomes translate to enhanced treatment planning, reduced anxiety for patients and their families, and ultimately, improved quality of life for those affected.
* Economic Considerations: The economic burden of brain tumors is staggering, encompassing direct medical costs, indirect costs related to lost productivity, and the long-term expenses associated with ongoing care. The economic motivation to adopt deep learning stems from its potential to optimize resource allocation, streamline diagnostic workflows, and contribute to more cost-effective and efficient healthcare delivery. By improving the accuracy of diagnoses and facilitating personalized treatment strategies, deep learning holds the promise of reducing the overall economic impact of brain tumors on healthcare systems and society at large.
* Technological Promise: The rapid advancements in deep learning techniques, fueled by the availability of large-scale datasets and computational resources, present an exciting technological promise. The ability of deep learning models to automatically learn and adapt from diverse and complex data makes them particularly well-suited for the intricate task of brain tumor classification. This technological promise serves as a motivator for researchers and practitioners to explore and harness the potential of these methodologies to elevate the standard of care in neuro-oncology.

In summary, the motivation to integrate deep learning into brain tumor classification is multifaceted, encompassing clinical imperatives, the human impact of brain tumors, economic considerations, and the transformative potential of advanced computational techniques. By addressing these motivations, this survey aims to contribute to the ongoing dialogue and collaborative efforts aimed at leveraging the power of deep learning for the benefit of individuals affected by brain tumors and society as a whole.

**1.3 Objectives:**

Against this backdrop, the primary objectives of this survey are twofold: first, to provide a comprehensive overview of the current state of brain tumor classification using deep learning, and second, to analyze the methodologies, architectures, and challenges inherent in this transformative field. By synthesizing existing knowledge, this survey aims to contribute to the global effort to combat brain tumors by empowering researchers, practitioners, and healthcare professionals with the tools and insights necessary to navigate the complexities of classification. Through these objectives, we aspire to foster continued innovation in medical imaging and contribute to the ongoing global endeavor to improve outcomes for those affected by brain tumors.

**2. Medical Imaging Modalities:**

**2.1 Magnetic Resonance Imaging (MRI):**

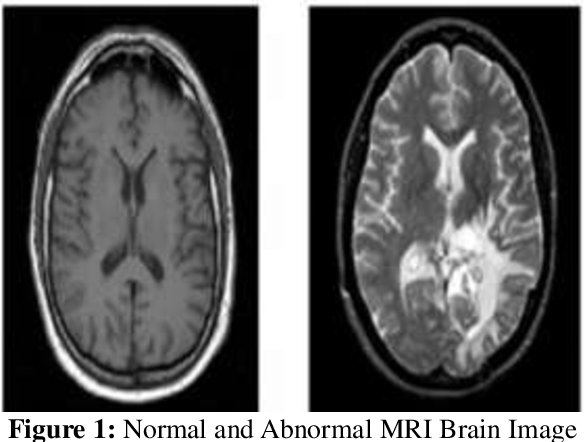
Magnetic Resonance Imaging (MRI) of the brain is a sophisticated process that generates three-dimensional image data, showcasing axial, sagittal, and coronal views at different depths. The characteristics of the images, such as quality, slice thickness, and the gap between slices, are influenced by both the strength of the magnetic field and the specific sampling protocols in use. When undergoing an MRI, the patient is positioned within a magnetic field remarkably stronger than Earth's magnetic field—nearly 10,000 times stronger. This intense field causes water protons in the body to align either in a parallel (low energy) or anti-parallel (high energy) orientation with the magnetic field.

To produce the desired images, a radiofrequency pulse is employed to disrupt the alignment of protons, resulting in the generation of a sinusoidal signal. This signal, subsequently detected by the scanner's antenna, plays a crucial role in creating the final image. The information conveyed in the image is contingent upon the behavior of mobile hydrogen protons, their speed, the time required for protons within the tissue to return to their original magnetization state (T1), and the duration for protons disturbed into coherent oscillation by the radiofrequency pulse to lose their coherence (T2) relaxation times.

The variations in T1 and T2 relaxation times among different tissues contribute to the contrast observed in T1-weighted (T1-w) and T2-weighted (T2-w) images. Notably, T1-w sequences feature a short repetition time (TR) and echo time (TE), causing tissues with shorter T1, such as white matter, to appear brighter compared to tissues with longer T1, like gray matter. Another imaging sequence, proton density-weighted (PD-w), combines a long TR from T2-w and a short TE from T1-w, with the resulting image formation being contingent upon the proton count.

In the field of MRI brain scan procedures, a range of techniques is available, including structural MRI, functional MRI, diffusion-weighted imaging (DWI), and diffusion tensor imaging (DTI). Structural MRI plays a crucial role in distinguishing between healthy and abnormal brain tissues based on their water content. This technique aids in visualizing various aspects of brain anatomy, such as tumoral vascularity, calcification, and radiation-induced micro hemorrhage. Structural sequences encompass T1-w, T2-w, FLAIR, and contrast-enhanced T1-w.

Functional MRI (fMRI) offers a distinctive perspective by capturing neural activity through the assessment of the ratio of oxygenated to deoxygenated blood during cognitive or motor tasks. This helps not only in localizing eloquent cortex regions but also in differentiating between tumor grades. Meanwhile, DWI focuses on characterizing tumors by examining the random motion of water molecules, thereby identifying cellularity, hypoxia, peritumoral edema, and distinguishing tumors located in the posterior fossa. Lastly, diffusion tensor imaging (DTI) provides a comprehensive analysis of the 3D diffusion direction, or diffusion tensor, of water molecules. This assists in determining the local effects of tumors on white matter tract integrity, including tract displacement, the presence of vasogenic edema, tumor infiltration, and tract destruction. The following figure displays the normal and abnormal image of brain captured by the MRI.



**Figure 1 -** the normal and abnormal MRI image of brain

**2.2 Computed Tomography (CT):**

The application of computed tomography (CT) scans in neuroimaging plays a crucial role in elucidating the functional and structural aspects associated with clinically significant signs of diseases. It is important to note, however, that while CT scans are valuable, they offer a more limited scope of information compared to magnetic resonance imaging (MRI), particularly in the diagnosis of brain tumors. This limitation arises from CT's inferiority to MRI in characterizing soft tissues like the brain, as well as its utilization of ionizing radiation.

Despite these limitations, a computed tomography (CT) scan excels in providing intricate details of bone structures adjacent to a brain tumor, such as the skull or spine. This capability makes CT scans particularly useful in cases where a more focused examination of bony anatomy is required. Additionally, a CT scan may serve as a viable alternative for diagnosing a brain tumor when magnetic resonance imaging (MRI) is not accessible or when the patient has implants, such as a pacemaker, which can interfere with MRI procedures.

Presently, computed tomography (CT) scans are frequently employed in the diagnosis of various medical conditions, including but not limited to acute hemorrhage, Parkinson's disease, head trauma, and determination of age. The versatility of CT scans makes them an indispensable tool in the medical field, offering valuable insights into diverse health-related scenarios. The following figure displays the image of brain captured by the CT scan.

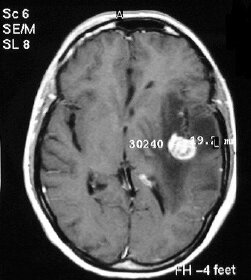


Figure 2 – CT image of brain

The subsequent sections of this paper are structured as follows: Section 3 provides an overview of related works in connection to this survey, outlining their strengths and limitations. Section 4 delves into the details of the literature search strategy, encompassing the chronological span, journal databases, keywords employed for the search, and the criteria applied for inclusion and exclusion. Moving on to Section 5, the focus is on elucidating the commonly utilized model performance metrics for evaluating the effectiveness of brain tumor segmentation and classification algorithms. Section 6 provides an overview of diverse deep learning models employed in brain tumor classification, along with the corresponding reported performance metrics. Section 7 sheds light on various brain tumor segmentation techniques, including region growing, conventional shallow supervised machine learning, and deep learning-based approaches. Furthermore, the discussion includes the presentation of reported performances associated with these techniques. Finally, Section 8 encapsulates the paper with a conclusive summary, summarizing the main points and potential implications drawn from the exploration of brain tumor segmentation and classification techniques.

**3 Related Works**

The pursuit of an improved autonomous technique for brain tumor segmentation and classification, with the potential to assist physicians in diagnosis, has been a dynamically evolving research domain. Consequently, numerous survey works have been undertaken to propel advancements in this field, summarizing the various techniques employed in brain tumor segmentation and classification. Table 1 exclusively features a selection of recent literature pertinent to our survey work. Additionally, a comprehensive analysis of their strengths and limitations is provided for clarity and insight.

**Table 1.** Survey literature on brain tumor segmentation and classification techniques.

|  |  |  |  |
| --- | --- | --- | --- |
| **Name** | **Method** | **Advantages** | **Disadvantage** |
| Classification of Brain Tumors from MRI Images Using a Convolutional Neural Network | A generic CNN model's performance is compared when original and augmented datasets are feeded into it, also they used record-wise and subject wise 10-fold cross validation | By using augmented dataset, the results are improved. | A small number of deep learning based brain tumor segmentation and classification literature are reviewed. Moreover Amount of original data |
| Brain Tumor Detection Based on Deep Learning Approaches and Magnetic Resonance Imaging | modified YOLO-V7 is used (YOLO-V7 + Convolutional Block Attention Module(CBAM) attention mechanism + Spatial Pyramid Pooling Fast+ (SPPF+) + Bi-directional Feature Pyramid Network (BiFPN) + decoupled head (DP)) | By coupling Yolo-V7 with other modules, the model performance is increased drastically | Addition of other modules made it more complex and increased computational parameters |
| A novel extended Kalman filter with support vector machine based method for the automatic diagnosis and segmentation of brain tumors | Model ensemble an Extended Kalman Filter (EKF) as well as Support Vector Machine (SVM) to categorize brain tumors in MR images. Finally, automatic segmentation method based on the combination of k-means  clustering and region growth is used for detecting brain tumors. | Better classification performance and effective segmentation | approach is computationally more complex as we are using region-growing algorithms |
| Brain tumor detection in MR image using superpixels, principal component analysis and template based K-means clustering algorithm | Initially, the important features were extracted utilizing the super pixels as well as principal component analysis (PCA), then followed by Template K-means clustering based segmentation | Template k-means algorithm provides better results than k-means | Lower classification accuracy |
| Brain tumor detection in MR image using superpixels, principal component analysis and template based K-means clustering algorithm | Initially, the important features were extracted utilizing the super pixels as well as principal component analysis (PCA), then followed by Template K-means clustering based segmentation | Template k-means algorithm provides better results than k-means | Lower classification accuracy |
| Brain tumor segmentation of MR images using SVM and fuzzy classifier in machine learning | Grey Level Run Length matrix (GLRLM) is used for feature extraction, classification is done using SVM algorithm. If tumor is detected, then using fussy c-means clustering algorithm along with other optimisation algorithms  to segment the tumor | improved analysis | This framework is less robust to alter different settings, namely slice thickness, imaging parameters, slice, contrast, etc. |
| Logistic Regression Machine Learning Algorithm On Mri Brain Image For Fast And Accurate Diagnosis | logistic regression is used as the ML algorithm to classify MR images in different classes based on the absence or presence of brain tumors | Early identification is possiable | while the alteration is done in the acquired data, another novel preparation data is needed |
| Improving Alzheimer’s Disease and Brain Tumor Detection Using Deep Learning with Particle Swarm Optimization | In the proposed model, initially input dataset is taken and CNN architecture is constructured but the parameters like LR,batch size,epochs,ect.. and size of convolution,pooling layers etcc are made variables. By using Particle swarm optimization algorithm, these variables are change and optimised to give the best results | Rather than trying all the combinations it is advantageous to use PSO algorithm to find the best parameter | Computatationally expensive and also, underlining model is simple CNN, intensity variations could change the outcome |
| Brain tumor segmentation of MR images using SVM and fuzzy classifier in machine learning | Grey Level Run Length matrix (GLRLM) is used for feature extraction, classification is done using SVM algorithm. If tumor is detected, then using fussy c-means clustering algorithm along with other optimisation algorithms to segment the tumor | improved analysis | Time consuming, as KNN takes more time for increase in features size |
| A Robust End-to-End Deep Learning-Based Approach for Effective and Reliable BTD Using MR Images | TumorResNet model, on basis of ResNet, using LeakyRelu as activation function | No vanishing gradient problem,less pre-processing | complex and limites intrepretability |
| An Ensemble Classification Method for Brain Tumor Images Using Small Training Data | image features are extracted using pretained CNN model. Next, ensembel classifier using SVM,MLP and few shot(FS) network is used for classification where final prediction is based on score-level fusion using SVM,weighted-sum,weighted-product | Requires small dataset for training | complex architecture and time consuming for processing |
| Brain Tumor Classification Using Conditional Segmentation with Residual Network and Attention Approach by Extreme Gradient Boost | Patch based technique is used for tumor segmentation using CNN. To improve segmentation CRF(conditional random field) is used. Then ResNet is used to generate feature and XG-boost is used for prediction | improved segmentation | Requires more time and space |
| DETECTION AND CLASSIFICATION OF MRI BRAIN TUMOUR USING GLCM AND ENHANCED K-NN | in proposed model, Fuzzy c-means is used for segmentation,GLCM for feature extraction and PCA for feature reduction. Finally Knn for prediction | simple architecture, improved segmentation | Time consuming |
| Explainable Artificial Intelligence for Human-Machine  Interaction in Brain Tumor Localization | Here, authors want to emphasis on Explainability and interpretability of AI model in brain tumor classification, as AI models perform as black box. To show case it they used 3 pre-trained models, trained on dataset and used Grad-CAM to verify the reason for the classification. | Using Grad-CAM, we can get to know how well the model is able to interpret the image | Despite having high accuracy, models were unable to exactly/approximately understand where the tumor is, and classifying them using some other non-irrelevant features |
| Computational Intelligence Approach to Improve  The Classification Accuracy of Brain Tumor Detection | Using CNN to identify tumor, if tumor is detected then again using preprocessing and watersged algorithm to calculate area of the tumor | Using preprocessing and segmentation algorithm on if tumor is detected, can reduce computational cost | Small tumors might not be detected |

Our endeavor is designed to offer an inclusive overview of recently introduced brain tumor segmentation and classification techniques, encompassing region growing, shallow machine learning, and deep learning methodologies. The compiled survey not only delves into the technical intricacies of these approaches but also addresses their respective strengths, weaknesses, and overall performance metrics.

**4 Method**

This survey extensively explores peer-reviewed research papers published between 2020 and 2023, specifically focusing on Scopus and Web of Science indexed journals. The investigation centers around the examination of brain tumor segmentation techniques utilizing region growing, deep learning-based approaches, as well as machine learning and deep learning-based methods for brain tumor classification. The survey encompasses a thorough search across various databases, namely MDPI, Science Direct, ResearchGate, and Google Scholar. The search criteria employed for this comprehensive survey are as follows: ("Brain Tumor") AND ("Classification") AND ("Machine Learning") AND ("Deep Learning") AND ("Segmentation") AND ("Region Growing"). The rigorous methodology for literature selection is explicitly outlined in Algorithm algorithm1. Additionally, Table 2 provides a detailed overview of the paper inclusion criteria (IC) guiding the selection process in this survey work.

|  |  |  |  |
| --- | --- | --- | --- |
| **Algorithm 1: Proposed Paper searching Technique:** | | | |
| **1** | BEGIN | | |
| **2** | Search ← MDPI, Science Direct, ResearchGate, and Google Scholar. | | |
| **3** | Set the search year range from 2020 to 2023 and include a few papers from previous years selectively, primarily to enhance the content of Section 1. | | |
| **4** | Initialize Variables N← 4, i← 1 | | |
| **5** | WHILE i ≤ N do | | |
| **6** |  | Keyword ← classification, deeplearning, segmentation, machinelearning, regiongrowing, braintumor | |
| **7** |  | if SearchLink ∈ Search and Year then | |
| **8** |  |  | Find (keyword)And ApplyInclusionCriteria← IC1, IC2 |
| **9** |  | end if | |
| **10** |  | Increment the t value by 1 | |
| **11** | END WHILE | | |
| **12** | Return the set of found papers. | | |
| **13** | END | | |

Table 2. Criteria for including papers in the selection process.

|  |
| --- |
| **inclusion criteria (IC)** |
| IC1: Papers must be published in journals indexed on either Scopus or Web of Science. |
| IC2: The paper should undergo a peer-review process. |

**5. Performance Measuring Metrics**

Evaluating how well a machine learning algorithm performs in segmenting and classifying is crucial in research. Sometimes, a model may seem good using one metric like accuracy, but it might not perform well with other metrics like precision. To better understand a model's performance, researchers often use various evaluation metrics. In segmentation tasks, true positive (TP) means the model correctly predicts a pixel belonging to a specific class according to the ground truth. True negative (TN) is when a pixel is correctly identified as not belonging to the given class. False positive (FP) happens when the model wrongly predicts a pixel not belonging to a class, and false negative (FN) is when the model wrongly predicts a pixel belonging to a class. For tumor classification, TP represents correctly predicting a tumor class according to the ground truth, while TN is correctly identifying a pixel not belonging to the tumor class. FP is when the model incorrectly predicts a tumor class not belonging to a given class, and FN is when the model incorrectly predicts the class belonging to a given class. Various performance metrics used in brain tumor segmentation and classification literature include:

Accuracy (ACC): Measures how well a model can correctly identify all classes or pixels, whether they are positive or negative.

Precision (PR), also referred to as positive predictive value (PPV), indicates how frequently the model correctly predicts a specific class or pixel. It reveals the accurate proportion of positive predictions made by the model.

Recall (RE) assesses how comprehensively the machine learning model's positive predictions align with the ground truth. It indicates the percentage of classes/pixels identified in our ground truth that are also present in the model's predictions.

Specificity (SPE) is the ratio of true negatives to the sum of true negatives and false positives. It indicates the percentage of classes/pixels that were not correctly identified.

Sensitivity (SEN) signifies the rate of accurately predicted positive samples or pixels among all genuine positive samples. It gauges the model's proficiency in recognizing positive samples or pixels.

The F1-Score, a widely used metric, combines both precision and recall by representing the harmonic mean of the two values.

The Dice similarity coefficient (DSC) evaluates the spatial concurrence between the ground truth tumor region and the model-segmented region. A DSC value of zero denotes no spatial overlap between the ground truth tumor region and the model's annotated result, while a value of one signifies complete overlap between the two.

**6 Brain Tumor Classification Methods**

According to the World Health Organization's (WHO) classification of central nervous system (CNS) tumors, there exist over 150 types of CNS tumors, primarily divided into primary and metastatic (secondary) tumors. Primary tumors originate within the brain or its immediate vicinity, while metastatic tumors stem from other body parts and migrate to the brain through the bloodstream. The metastatic tumors are generally considered malignant or cancerous, whereas primary tumors can manifest as either benign or malignant. The conventional gold standard for brain tumor classification is a biopsy, which necessitates definitive brain surgery for obtaining a tissue sample. In contrast, automated brain tumor classification from an MRI offers a non-invasive alternative, eliminating the need for invasive procedures and enhancing safety. Moreover, machine learning-based brain tumor classification using MRI scans has the potential to advance the accuracy of diagnosis and treatment planning. Consequently, the automated classification of brain tumors from MRI images using machine or deep learning techniques has emerged as a vibrant area of research, yielding promising results.

The traditional machine learning-based brain tumor classification techniques often consist of preprocessing, segmentation, feature extraction, and classification stages.

**6.1 Pre-processing**

Various noises, such as salt and pepper, Gaussian, Rician, and speckle noise, significantly impact brain MRI scans. These noise types pose challenges in machine learning applications. Consequently, achieving high-quality image denoising becomes a crucial objective during the pre-processing phase. Each MRI denoising method comes with its own set of advantages and disadvantages. Numerous techniques have been devised to mitigate noise by leveraging statistical properties and frequency spectrum distribution. Beyond denoising, pre-processing tasks encompass tag removal, foreground region smoothing, intensity inhomogeneity correction, preservation of relevant edges, resizing, cropping, and skull stripping. In addition to denoising, tasks such as removing tags, smoothing the foreground region, intensity inhomogeneity correction, maintaining relevant edges, resizing, cropping, and skull stripping are part of pre-processing.

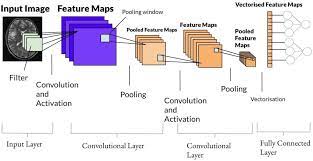
**6.2 Region of interest(ROI) Detection:**

In the context of an MRI brain scan, the segmentation process involves assigning labels to individual voxels within the MRI image, indicating their respective tissue types and anatomical structures. The goal of detecting Regions of Interest (ROI) in tumor classification is to precisely identify the tumor area in an MRI scan. This enhances visualization, facilitating quantitative measurements of image structures during the feature extraction phase. Brain tumor segmentation can be executed through three distinct approaches: manual segmentation, semi-automatic segmentation, and fully automatic segmentation.

**6.3 Various classification method:**

**6.3.1 Convolutional Neural Networks (CNNs):**

Convolutional Neural Networks (CNNs) have emerged as a pivotal class of deep learning architectures for image-based tasks, including brain tumor classification. The distinctive feature of CNNs lies in their ability to automatically learn hierarchical representations from input data. This is achieved through the application of convolutional operations, pooling layers, and non-linear activation functions. In the context of brain tumor classification, CNNs excel at capturing intricate spatial relationships and local features within medical images, making them well-suited for this intricate task.



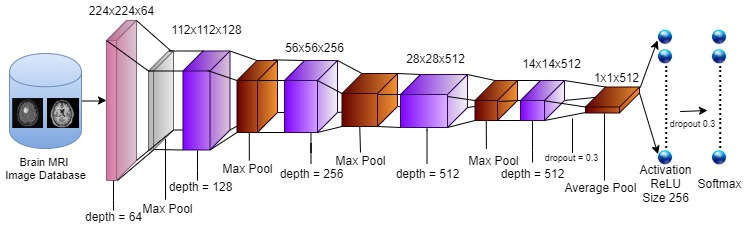
**6.3.2 Recurrent Neural Networks (RNNs):**

Recurrent Neural Networks (RNNs) are well-suited for sequential data, and while not as commonly applied in brain tumor classification, they find relevance in cases where the temporal evolution of the tumor or the sequential nature of imaging data is crucial. RNNs utilize recurrent connections to capture dependencies over time, enabling them to model sequential patterns effectively. In the context of brain tumor classification, RNNs could be applied to sequences of medical images, such as those obtained from dynamic imaging modalities.

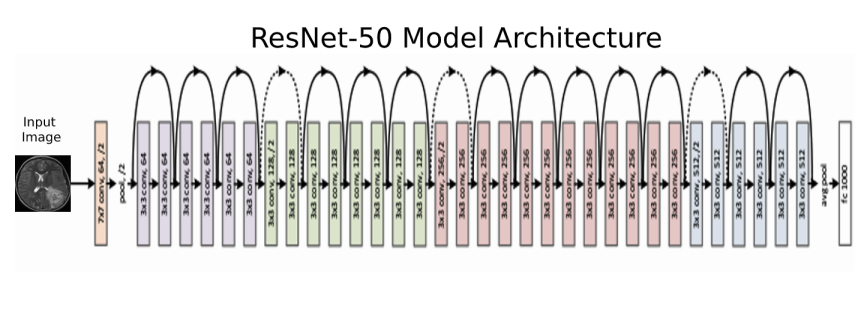
**6.3.3Transfer Learning:**

Transfer learning has become a cornerstone in leveraging pre-trained models for brain tumor classification, enabling the effective utilization of knowledge gained from large datasets in related domains. In this section, we delve into some of the prominent architectures often employed in transfer learning for medical imaging tasks.

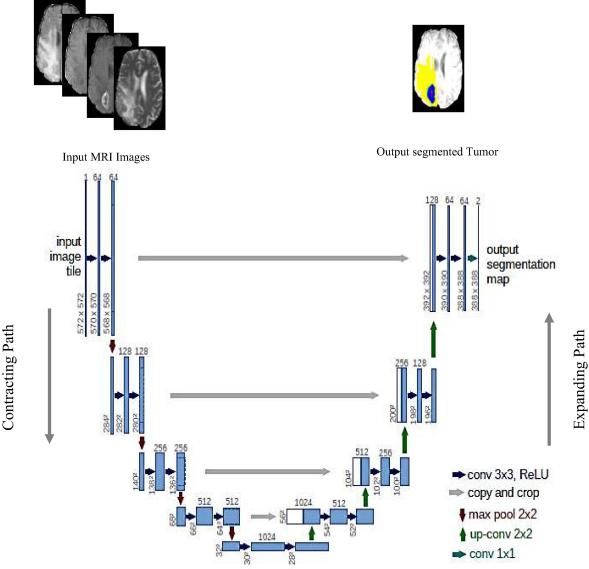
**VGG-16:** VGG-16 is renowned for its simplicity and effectiveness. It comprises 16 convolutional layers, featuring small 3x3 filters with a stride of 1. Transfer learning involves using the pre-trained VGG-16 model on large image datasets (e.g., ImageNet) and fine-tuning it for brain tumor classification. The model has shown transferability, even when applied to medical images with distinct characteristics.



**ResNet:** Residual Networks (ResNets) introduced a novel architecture with shortcut connections, addressing the vanishing gradient problem. These connections enable the flow of gradients directly through the network, facilitating the training of extremely deep networks. In transfer learning, ResNet models, particularly ResNet-50 and ResNet-101, have demonstrated robust performance in feature extraction for brain tumor classification tasks.



**U-Net:** U-Net is a convolutional neural network architecture designed for semantic segmentation tasks. Its unique U-shaped architecture allows for the incorporation of high-resolution contextual information during both the encoding and decoding phases. In transfer learning, U-Net has been adapted for tasks such as brain tumor segmentation, showcasing its versatility in medical image analysis.



**Advantages and Disadvantages:**

|  |  |  |
| --- | --- | --- |
| **Architecture** | **Advantages** | **Disadvantages** |
| VGG-16 | -Simplicity and ease of understanding  -Transferability to medical imaging tasks.  -Effective feature extraction capabilities. | -Relatively higher computational requirements.  -Prone to overfitting, especially on smaller datasets. |
| ResNet | -Ability to train very deep networks.  -Mitigation of vanishing gradient problem through shortcut connections.  -High feature extraction capabilities. | -Increased model complexity.  -More challenging interpretability compared to shallower architectures. |
| U-Net | -Designed for semantic segmentation tasks, ideal for medical image segmentation.  -Efficient use of contextual information.  -Versatile architecture. | -Limited applicability to tasks beyond segmentation.  -May require additional post-processing steps. |

This comprehensive exploration of CNNs, RNNs, and transfer learning architectures, such as VGG-16, ResNet, and U-Net, lays the foundation for understanding the nuances of deep learning methodologies in the context of brain tumor classification.

**Summary of deep learning based brain tumor classification techniques**

|  |  |  |
| --- | --- | --- |
| **Paper** | **Method** | **Performance** |
| Badža, M.M.; Barjaktarović, M.Č. Classification of Brain Tumors from MRI Images Using a Convolutional Neural Network. | Custom CNN model | Accuracy - 91.9% |
| Ge, C.; Gu, I.Y.H.; Jakola, A.S.; Yang, J. Enlarged Training Dataset by Pairwise GANs for Molecular-Based Brain Tumor Classification | Multi-stream 2D-CNN model | Accuracy - 88.82% |
| Ge, C.; Gu, I.Y.H.; Jakola, A.S.; Yang, J. Enlarged Training Dataset by Pairwise GANs for Molecular-Based Brain Tumor Classification | Custom CNN model | Accuracy - 97.54% |
| Huang, Z.; Du, X.; Chen, L.; Li, Y.; Liu, M.; Chou, Y.; Jin, L. Convolutional Neural Network Based on Complex Networks for Brain Tumor Image Classification With a Modified Activation Function | Convolutional Neural Network based on Complex Networks | Accuracy - 95.49% |
| Ucuzal, H.; YASAR, S.; Colak, C. Classification of brain tumor types by deep learning with convolutional neural network on magnetic resonance images using a developed web-based interface | AutoML | Accuracy - 96.2% |
| Noreen, N.; Palaniappan, S.; Qayyum, A.; Ahmad, I.; Imran, M.; Shoaib, M. A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor. | Iception-V3 DensNet201 | Accuracy - inception - 99.34%  Accuracy - inception - 99.51% |
| Rehman, A.; Naz, S.; Razzak, M.I.; Akram, F.; Imran, M. A Deep Learning-Based Framework for Automatic Brain Tumors Classification Using Transfer Learning | AlexNet, GoogleNet & VGG16 | Accuracy - AlexNet - 95.46% Accuracy - GoogleNet - 98.04% Accuracy - VGG16 - 98.69% |
| Rehman, A.; Naz, S.; Razzak, M.I.; Akram, F.; Imran, M. A Deep Learning-Based Framework for Automatic Brain Tumors Classification Using Transfer Learning | CapsulNet | Precision - 85% |
| Díaz-Pernas, F.J.; Martínez-Zarzuela, M.; Antón-Rodríguez, M.; González-Ortega, D. A Deep Learning Approach for Brain Tumor Classification and Segmentation Using a Multiscale Convolutional Neural Network | Multiscale CNN | Accuracy - 97.3% |
| Díaz-Pernas, F.J.; Martínez-Zarzuela, M.; Antón-Rodríguez, M.; González-Ortega, D. A Deep Learning Approach for Brain Tumor Classification and Segmentation Using a Multiscale Convolutional Neural Network | DNN | Accuracy - 96.15% |
| Díaz-Pernas, F.J.; Martínez-Zarzuela, M.; Antón-Rodríguez, M.; González-Ortega, D. A Deep Learning Approach for Brain Tumor Classification and Segmentation Using a Multiscale Convolutional Neural Network | Custom CNN model | Accuracy - 84.19% |
| Sharif, M.I.; Khan, M.A.; Alhussein, M.; Aurangzeb, K.; Raza, M. A decision support system for multimodal brain tumor classification using deep learning | Pre-trained DenseNet201 | Accuracy - 99.8% |
| Naser, M.A.; Deen, M.J. Brain tumor segmentation and grading of lower-grade glioma using deep learning in MRI images. | VGG16 | Accuracy - 89% |

**6.4 various Image Segmentation techniques:**

**Image Segmentation and its importance:**

Image segmentation is a fundamental task in medical image analysis, including brain tumor classification. It involves partitioning an image into meaningful and homogeneous regions, enabling a more detailed analysis of specific structures or objects. In the context of brain tumor classification, segmentation plays a crucial role in delineating tumor boundaries, aiding in treatment planning, and facilitating quantitative analysis of tumor characteristics. Accurate segmentation is essential for extracting relevant features and improving the overall performance of machine learning models in medical imaging.

**Segmentation Techniques:**

**6.4.1 Improved K-Means Clustering:** K-Means clustering is a widely used method for image segmentation. The improved version incorporates spatial information to enhance segmentation accuracy. By considering both intensity and spatial proximity, improved K-Means clustering mitigates the sensitivity to noise and better captures local structures in medical images.

**6.4.2 Fuzzy C-Means Clustering:** Fuzzy C-Means clustering introduces the concept of fuzziness, allowing pixels to belong to multiple clusters with varying degrees of membership. This approach is advantageous when dealing with the inherent ambiguity in medical images. In brain tumor segmentation, fuzzy clustering enables a more nuanced representation of tissue characteristics.

**6.4.3 Threshold and Fuzzy Thresholding:** Thresholding is a simple yet effective segmentation technique. Setting a threshold value separates pixels into distinct regions based on intensity. Fuzzy thresholding extends this idea by considering the degree of membership of pixels to different intensity classes, allowing for a smoother transition between regions. These methods are particularly useful for binary segmentation tasks.

**6.4.4 Global Thresholding**: Global thresholding involves determining a single threshold value for the entire image. While computationally efficient, it may struggle with images exhibiting significant intensity variations. In brain tumor segmentation, global thresholding can be effective when tumors have distinct intensity differences from surrounding tissues.

**6.4.5 Watershed Algorithm:** The watershed algorithm views an image as a topographic surface, where pixel intensities represent elevations. Watershed lines separate regions analogous to watersheds separating hills. This algorithm is valuable in segmenting objects with distinct boundaries, making it applicable to tumor segmentation. However, careful pre-processing is often needed to prevent over-segmentation.

**Comparison of Segmentation Techniques:**

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| --- | --- | --- |
| Technique | Advantages | Disadvantages |
| Improved K-Means | - Incorporates spatial information for better accuracy.  - Robust to noise. | - Sensitive to initialization, may converge to local minima.  - Computationally intensive for large datasets. |
| Fuzzy C-Means | - Handles ambiguity in pixel assignments through fuzziness.  - Effective in capturing complex tissue characteristics. | - Computational complexity increases with the number of clusters.  - Sensitivity to noise and outliers. |
| Threshold and Fuzzy Thresholding | - Simple and computationally efficient.  - Suitable for binary segmentation tasks. | - Sensitive to variations in intensity and contrast.  - Challenging for images with non-uniform illumination. |
| Global Thresholding | - Straightforward and computationally efficient.  - Applicable when global intensity differences are pronounced. | - Limited adaptability to images with varying intensity.  - May result in inaccurate segmentation for complex structures. |
| Watershed Algorithm | - Effectively captures distinct boundaries between objects.  - Applicable to images with well-defined intensity gradients. | - Prone to over-segmentation without proper pre-processing.  - Sensitive to noise and irregularities in the image. |

In summary, image segmentation techniques, including improved K-Means clustering, fuzzy clustering means, thresholding, fuzzy c-means clustering, global thresholding, and the watershed algorithm, offer diverse approaches to extract meaningful regions in medical images. The choice of technique depends on the characteristics of the image and the specific segmentation goals. Improved K-Means and fuzzy clustering methods address some of the limitations of traditional approaches, while thresholding methods provide simplicity and efficiency. The watershed algorithm is valuable for segmenting objects with well-defined boundaries. Understanding the strengths and weaknesses of these techniques is crucial for their effective application in brain tumor segmentation.

**Summary of deep learning based brain tumor segmentation techniques**

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| --- | --- | --- |
| **Paper** | **Method** | **Performance** |
| Pereira, S.; Pinto, A.; Alves, V.; Silva, C.A. Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images | Custom CNN model | Dice similarity coefficient- 88% |
| Deng, W.; Shi, Q.; Wang, M.; Zheng, B.; Ning, N. Deep Learning-Based HCNN and CRF-RRNN Model for Brain Tumor Segmentation. | Heterogeneous CNN + Conditional Random Fields-Recurrent Regression based Neural Network | Accuracy - 98.6% |
| Ding, Y.; Li, C.; Yang, Q.; Qin, Z.; Qin, Z. How to Improve the Deep Residual Network to Segment Multi-Modal Brain Tumor Images | Residual Network+ Dilated convolution RDM-Net | Dice similarity coefficient - 86%% |
| Ali, M.; Gilani, S.O.; Waris, A.; Zafar, K.; Jamil, M. Brain Tumour Image Segmentation Using Deep Networks | Ensemble of a 3D-CNN and U-net | Dice similarity coefficient - 90.6% |
| Aboelenein, N.M.; Songhao, P.; Koubaa, A.; Noor, A.; Afifi, A. HTTU-Net: Hybrid Two Track U-Net for Automatic Brain Tumor Segmentation | Hybrid two track U-Net (HTTU-Net) | Dice similarity coefficient - 86.5% |
| Wang, G.; Li, W.; Zuluaga, M.A.; Pratt, R.; Patel, P.A.; Aertsen, M.; Doel, T.; David, A.L.; Deprest, J.; Ourselin, S.; et al. Interactive Medical Image Segmentation Using Deep Learning With Image-Specific Fine Tuning | P-Net with bounding box and image specific fine tunning (BIFSeg) | Dice similarity coefficient - 86.29% |
| Zhou, T.; Canu, S.; Ruan, S. Fusion based on attention mechanism and context constraint for multi-modal brain tumor segmentation. | Cascaded 3D U-nets | Dice similarity coefficient - 89.4% |
| Ye, F.; Zheng, Y.; Ye, H.; Han, X.; Li, Y.; Wang, J.; Pu, J. Parallel pathway dense neural network with weighted fusion structure for brain tumor segmentation | 3D Center-crop Dense Block | Dice similarity coefficient - 88.9% |
| Naser, M.A.; Deen, M.J. Brain tumor segmentation and grading of lower-grade glioma using deep learning in MRI images | U-Net | Dice similarity coefficient - 84.0% |
| Li, H.; Li, A.; Wang, M. A novel end-to-end brain tumor segmentation method using improved fully convolutional networks | Inception-based U-Net + up skip connection + cascaded training strategy | Dice similarity coefficient - 89.0% |

1. **Discussion:**

This paper provides a comprehensive review of methodologies employed in the segmentation and classification of brain tumors. The survey covers a range of traditional machine learning and deep learning approaches, accompanied by their quantitative performance metrics.This paper provides a comprehensive review of methodologies employed in the segmentation and classification of brain tumors. The survey covers a range of traditional machine learning and deep learning approaches, accompanied by their quantitative performance metrics.Conventional image processing and shallow machine learning techniques are becoming outdated due to the rise of deep learning. Deep learning models perform end-to-end tumor segmentation by processing MRI images through their building blocks, automatically extracting descriptive information without relying on handcrafted features. However, challenges include the need for large datasets for training and model interpretability issuesBeyond tumor segmentation, classifying tumors into histological types is crucial for diagnosis and treatment planning, often requiring biopsy. Shallow machine learning algorithms involve preprocessing, ROI detection, and feature extraction. However, due to MRI noise sensitivity and variations in tumor characteristics, extracting descriptive information is challenging. Presently, deep learning techniques are emerging as the state-of-the-art for classifying various brain tumor types, such as astrocytoma, glioma, meningioma, and pituitary tumors. The paper discusses several brain tumor classification methods, summarized earlier.

1. **Challenges in Brain Tumor Identification and Classification:**

Identifying and classifying brain tumors using deep learning poses several challenges, as the task involves complex medical imaging data and the need for accurate and timely diagnoses. Some of the key challenges in brain tumor identification and classification using deep learning include

1. Limited Annotated Data:

The availability of well-annotated medical imaging data for brain tumors remains a significant challenge. Limited datasets can hinder the development and training of robust machine learning models.

1. Inter-observer Variability:

The subjective nature of manual annotations by different clinicians can lead to inter-observer variability, affecting the reliability of ground truth labels and subsequently impacting model training.

1. Heterogeneity of Tumor Types:

Brain tumors exhibit diverse histological and molecular characteristics. Developing models that can effectively classify various tumor types, considering this heterogeneity, is a complex challenge.

1. Explainability and Interpretability:

Deep learning models, while achieving high accuracy, often lack interpretability. Ensuring that these models provide clinically interpretable results is crucial for gaining trust from healthcare professionals.

1. Real-time Deployment:

Deploying efficient and accurate models for real-time brain tumor classification in clinical settings poses challenges, especially given the computational resources required for complex deep learning architectures.

1. Generalization Across Datasets:

Ensuring the generalization of models across different datasets, acquired from various imaging modalities and institutions, remains a challenge due to variations in acquisition protocols and equipment.

1. **Future Directions in Brain Tumor Identification and Classification:**

We have seen some of the challenges present in using Deep learning for Brain tumor identification and classification. Despite that there is several possibilities that can be adapted to make significant progress. Some of them are:

1. Multimodal Integration:

Future research should explore the integration of multimodal data, combining information from diverse imaging techniques such as MRI, CT, and PET scans. This approach can potentially enhance the accuracy and robustness of brain tumor classification models.

1. Explainable AI in Healthcare:

Developing interpretable and explainable deep learning models is crucial for gaining the trust of clinicians. Future work should focus on creating models that provide insights into decision-making processes, increasing their adoption in clinical practice.

1. Transfer Learning Strategies:

Investigating advanced transfer learning strategies, including domain adaptation and cross-modality transfer learning, can help improve the generalization of models to diverse datasets and clinical scenarios.

1. Incorporating Genomic and Molecular Data:

Integrating genomic and molecular data into brain tumor classification models can provide a more comprehensive understanding of tumor characteristics. This can contribute to personalized treatment strategies and prognosis prediction.

1. Addressing Data Imbalance:

Developing strategies to handle imbalances in class distributions, especially for rare tumor types, is essential for creating models that are equitable in their predictions across different patient groups.

1. Collaborative Efforts and Standardization:

Encouraging collaboration among researchers and standardizing data acquisition protocols can contribute to the creation of larger, more diverse datasets. This can address the challenge of limited annotated data and facilitate the development of robust models.

1. Ethical Considerations:

Future research should place a strong emphasis on addressing ethical considerations related to the deployment of machine learning models in healthcare. This includes issues related to patient privacy, consent, and the responsible use of AI in clinical decision-making.

By addressing these challenges and pursuing these future directions, the field of brain tumor classification can make significant strides towards developing reliable, interpretable, and widely applicable models that positively impact clinical practice and patient outcomes.

1. **Conclusion:**

In conclusion, the field of brain tumor classification has witnessed significant advancements driven by the integration of deep learning, optimization techniques, and innovative segmentation methods. The experimental evaluation of these models on diverse datasets has shown promising results, with notable achievements in accuracy, precision, and recall. However, several challenges persist, including the scarcity of annotated data, inter-observer variability, and the need for models that are both accurate and interpretable.

As we move forward, addressing these challenges is paramount. Future research directions focus on multimodal integration, explainable AI, advanced transfer learning strategies, and the incorporation of genomic and molecular data. Collaborative efforts, standardization of data, and ethical considerations will play pivotal roles in advancing the field responsibly.

The journey towards effective brain tumor classification involves a dynamic interplay of computational methodologies and a deep understanding of the intricacies of medical imaging. By embracing these challenges and exploring new avenues, researchers and clinicians can collectively contribute to the development of robust, generalizable, and clinically relevant models, ultimately enhancing the diagnosis and treatment of brain tumors.

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