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Comparison of Machine Learning Techniques for Segmentation of Spinal Cord Tumors from MR Images

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Abstract: - Precise detection and segmentation of spinal cord tumors from magnetic resonance imaging (MRI) assume a crucial part in boosting clinical examination applications. To capture intricate tumor details, recent techniques have made use of multi-modal imaging, which incorporates the T1, T1c, T2, and FLAIR modalities. While a considerable lot of these methodologies show promising outcomes on benchmark datasets like Brats2018, hurdles continue to arise because of the inherent intricacy, demanding significant training and testing times. A novel strategy is proposed to improve the adaptability and efficiency of spinal cord tumor segmentation in response to these difficulties. To start, a Cascade Deep Learning model's overfitting and computational demands are reduced by introducing a preprocessing method that focuses only on a small area of the image. In this way, an original Cascade Convolutional Brain Network (C-ConvNet/C-CNN) is introduced, decisively intended to remove both local and global features through unique routes. To additionally further develop segmentation accuracy past existing state-of-the-art models, a pivotal Distance-Wise Attention (DWA) system is presented. The DWA component considers the spatial connection between the tumor location and the encompassing brain structures, upgrading the accuracy of growth depiction. The proposed model's efficacy is demonstrated by extensive testing on the BRATS 2018 dataset. The outcomes feature competitive results, with mean whole tumor, enhanced tumor, and tumor core dice scores of 0.9203, 0.9113, and 0.8726, separately. Quantitative and qualitative assessments are presented and discussed, highlighting the effectiveness of the proposed strategy in spinal cord tumor segmentation from MRI images. This exploration adds to the continuous endeavours in propelling AI methods for clinical image investigation, offering an important stratagem for clinicians and scientists in the field.

Keywords: Spinal Cord Tumors, MRI Segmentation, Machine Learning, Multimodal Imaging, Cascade Convolutional Neural Networks,

I. INTRODUCTION

Brain tumors stand as a formidable global health challenge, with gliomas emerging as the predominant primary brain tumors. These tumors originate from the abnormal growth of glial cells in the spinal cord and brain, presenting diverse histological and malignancy grades. Glioblastoma, a particularly aggressive subtype of glioma, carries a fatal prognosis, with an average survival of less than 14 months post-diagnosis. The diagnostic foundation, Magnetic Resonance Imaging (MRI), provides rich tissue contrasts across modalities, facilitating brain tumor diagnosis for medical specialists.

However, the intricate task of manually segmenting and analysing structural MRI images of brain tumors remains a laborious endeavour, exclusive to skilled neuroradiologists. The need for an automatic and robust brain tumor segmentation approach is evident, promising significant impacts on diagnosis and treatment. Beyond its application in brain tumor scenarios, such automatic segmentation holds the potential to usher in timely interventions for neurological disorders like Alzheimer’s disease, schizophrenia, and dementia. Automated lesion segmentation techniques offer invaluable support to radiologists, furnishing crucial insights into tumor volume, localization, and shape, encompassing both enhancing tumor core regions and the entirety of tumor regions. Overcoming challenges inherent in medical imaging analysis, such as disparities in size, bias field artifacts arising from suboptimal image acquisition, as well as variations in location and shape, highlights the pressing need for advanced methodologies in the pursuit of more effective and meaningful therapeutic progress.

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II. Literature Review

Advancements in the field of medical imaging, particularly in the segmentation of brain and spinal tumors, have been significantly influenced by the annual BraTS challenge. Notable progress has been achieved through the deployment of convolutional neural networks (CNNs), as demonstrated by top-performing models such as those developed by Havaei et al. (2017), Isensee et al. (2017, 2019), Kamboj et al. (2018), and Naceur et al. (2018). However, the distinction between brain and spinal tumors necessitates distinct processing methodologies due to variations in size and anatomical characteristics. Unlike the brain, the spinal cord presents unique challenges, primarily attributed to its smaller diameter and elongated shape. The spinal cords average diameter, measured at its largest point, is approximately 13.3 ± 2.2 mm, with lengths ranging from 420 to 450 mm. This dimensional difference introduces complexities in deciding optimal cropping and patch sizes for accurate segmentation. Additionally, spinal cord imaging encounters challenges associated with respiratory and cardiac motion artifacts, as reported by Stroman et al. (2014). Furthermore, segmentation of spinal tumors faces added complexity due to their interfaces with cerebrospinal fluid, particularly on T2-weighted scans, where fluid appears hyperintense, making it challenging to differentiate from pathological presentations.

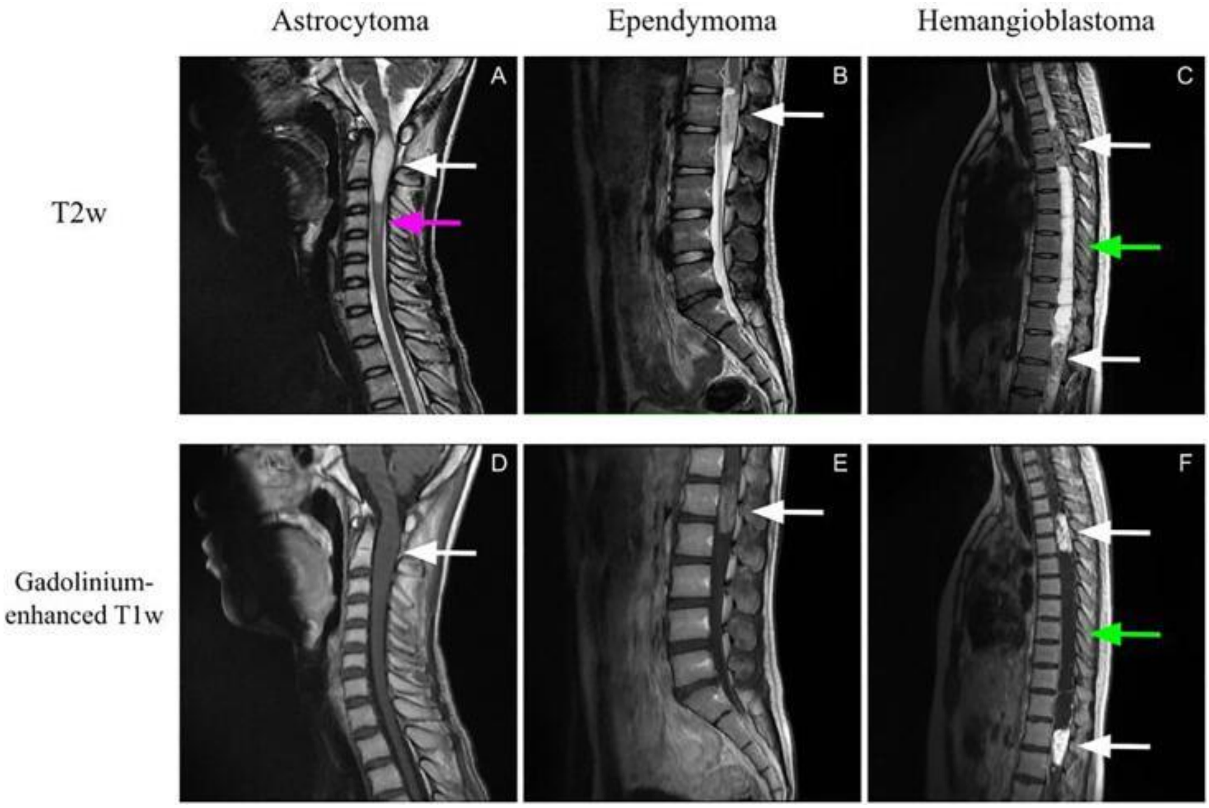

Figure 1. Intramedullary spinal cord tumors (IMSCT) exhibit considerable heterogeneity in terms of forces, size, and longitudinal area, as depicted in the presented images. The top row (A, B, C) corresponds to T2-weighted (T2w) scans, while the bottom row (D, E, F) displays gadolinium-enhanced T1-weighted (T1w) images. The initial segment (A, D) provides an illustrative representation of astrocytoma, the subsequent segment (B, E) showcases an example of ependymoma, and the final segment (C, F) features an illustration of hemangioblastoma. Solid tumor components are indicated by white arrows, liquid-filled cavities by green arrows, and areas of edema by pink arrows. This comprehensive imaging approach offers insights into the diverse characteristics and structural variations present in different types of intramedullary spinal cord tumors.

In the realm of spinal tumor models, recent studies have made noteworthy contributions. Hille et al. (2020) developed a U-Net-based model specifically for segmenting spine metastases, achieving a commendable Dice score of 77.6% on average. Reza et al. (2019) introduced a cascaded architecture tailored for spine chordoma tumor segmentation, a rare tumor type typically found in bone near the spinal cord and the skull base, demonstrating a median absolute difference of 48%. While these models address spine tumors, it is crucial to note that they are single-class models focused on tumor segmentation only. Their applicability to intramedullary spinal cord tumors (IMSCT) is limited due to the distinct intensities, sizes, and juxtaposition with different tissue types, such as bone tissue versus neuronal tissue. Furthermore, the lack of publicly available pre-trained models impedes direct utilization by the medical community, hindering the application of these models to new and diverse datasets. Various models aiming to delineate accurate and efficient boundary curves of brain tumors in medical images have been explored in the literature, categorizing into three main groups:

A. Machine Learning Approaches

Machine learning strategies tackle segmentation challenges by predominantly leveraging hand-crafted features or pre-defined features. In this paradigm, the initial step involves extracting key information from input images using feature extraction algorithms. Subsequently, a discriminative model is trained to distinguish tumors from normal tissues. Methods within this category often employ hand-crafted features in conjunction with classifiers like random forests, support vector machines (SVM), and fuzzy clustering. However, the necessity for time-consuming feature extraction, especially in scenarios with fuzzy or vague boundaries between healthy tissues and tumors, can lead to suboptimal performance.

B. Multi-Atlas Registration (MAS) Algorithms

Multi-atlas registration algorithms operate on the principles of registering and fusing labels from multiple normal brain atlases onto a new image modality. Despite their potential, MAS algorithms face challenges in the registration of normal brain atlases and require a substantial number of atlases, limiting their applicability in tasks demanding speed.

C. Deep Learning Methods

Deep learning techniques represent a paradigm shift by automatically extracting crucial features. These approaches have demonstrated exceptional results across various domains and have been particularly successful in brain tumor segmentation. Noteworthy models include the TSBTS network, which mimics physician expertise by exploring both task-modality and task-task structures for dissimilar tumor region identification. Other approaches incorporate generative adversarial networks (GANs) for knowledge transition across different modality data and the introduction of innovative network architectures, such as OM-Net and AssemblyNet, which address challenges like imbalanced data and limited training datasets. These models efficiently extract both local and global contextual features, showcasing advancements in deep convolutional neural network structures for robust brain tumor segmentation.

III. METHODOLOGY

The accurate diagnosis of neoplastic lesions in the spinal cord is paramount for effective treatment and prognosis determination. Researchers in the biomedical and bioinformatics fields have explored the potential of various machine learning methods to improve classification accuracy, with a focus on intramedullary spinal cord tumors.

Efforts to differentiate these tumors from inflammatory demyelinating lesions have led to innovative approaches. Zhuo et al. introduced a deep learning pipeline utilizing T2-weighted magnetic resonance images, outperforming experienced neuroradiologists in certain instances. Their two-dimensional MultiResUNet and DenseNet121 networks achieved remarkable accuracy, particularly in distinguishing between tumors and inflammatory lesions.

Incorporating patient clinical information into radiological diagnoses, Liu et al. proposed a weighted fusion framework on magnetic resonance imaging. This framework, incorporating tumor detection, sequence classification, and age information, demonstrated superior accuracy compared to traditional diagnostic methods, showcasing the potential of artificial intelligence to enhance clinical decision-making.

Machine learning techniques, particularly deep learning, have also been applied to diagnose extramedullary tumors. Maki et al. and Ito et al. utilized convolutional neural network architectures on magnetic resonance images to achieve diagnostic accuracy rates comparable to experienced radiologists. Cao et al. introduced a novel convolutional neural network-based deep learning model, surpassing conventional radiomic methods and radiologists' assessments in classifying malignant nerve sheath tumors from spinal schwannomas.

Beyond diagnosis, machine learning techniques have been instrumental in understanding the molecular and genetic profiles of spinal cord tumors. Jung et al. used a random forest model to predict H3 K27M mutations based on clinical and radiological data, while Pandey et al. developed a machine learning method to distinguish driver and passenger mutations in glioblastoma. These approaches provide valuable insights into prognostic factors and potential therapeutic targets.

Moreover, machine learning has proven effective in automating the interpretation of histopathology, identifying mutations such as IDH1, MGMT promoter methylation, and 1p19q codeletion. The application of machine learning in intraoperative histopathologic specimens demonstrates its potential to assist neuropathologists in complex cases, enhancing diagnostic accuracy.

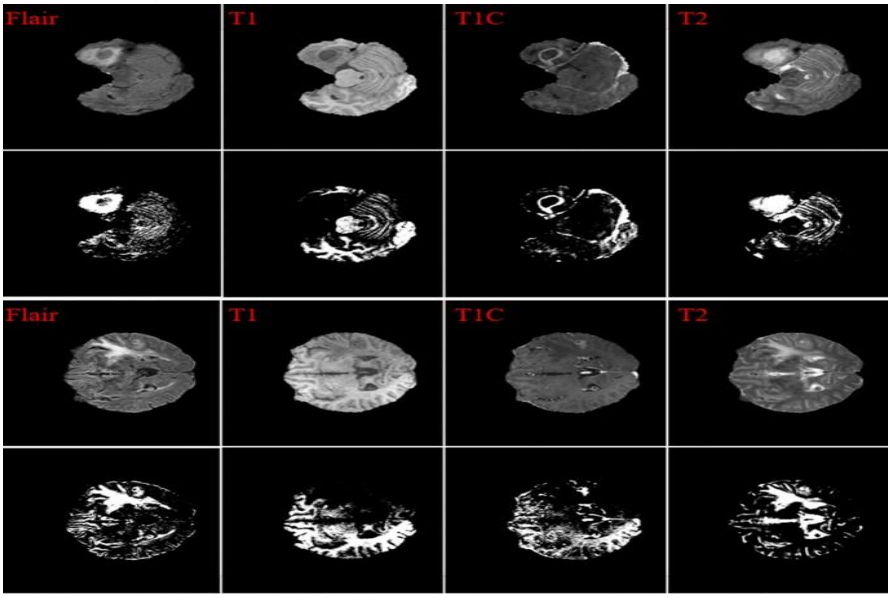

Figure 2: Two arrangements of four MRI modalities and their relating Z-Score standardization

In conclusion, machine learning plays a pivotal role in advancing diagnostic capabilities for spinal cord tumors. Its applications in classification, segmentation, and molecular profiling offer significant improvements over traditional methods. As these techniques continue to evolve, the integration of artificial intelligence in radiological imaging, histopathology, and genomics is poised to revolutionize clinical practice, providing accurate predictions and warning alerts to aid healthcare professionals in decision-making.

In the realm of spinal cord tumor management, surgical intervention aims not only to restore neurological function and enhance quality of life but also to minimize the risks associated with surgery, emphasizing the importance of achieving gross total resection to reduce the likelihood of tumor recurrence. Leveraging machine learning, Khan et al. demonstrated its potential in predicting health-related quality of life outcomes post-surgery for patients with mild degenerative cervical myelopathy. By employing various machine learning algorithms and considering demographic, clinical, and surgical approach-related factors, their model provides a basis for tailoring surgical strategies to individual patients, offering a personalized and optimized approach.

Surgical planning, a critical phase in patient-specific management, stands to benefit significantly from artificial intelligence. The evolving field of machine learning in surgical planning takes advantage of advanced image processing capabilities to accommodate anatomical variations among patients. Jakubicek et al.'s work on localization using convolutional neural networks exemplifies this progress, demonstrating successful identification and labeling of vertebrae in distorted and incomplete spine scans. The ability of machine learning to adapt to suboptimal data enhances its clinical utility, showcasing its potential to revolutionize surgical planning by accounting for individual patient variations.

Resection of spinal cord tumors presents unique challenges, particularly with infiltrative tumors. Machine learning, exemplified by Marcus et al.'s artificial neural network, enhances the prediction of surgical respectability, aiding surgeons in optimizing tumor removal while minimizing damage to normal tissue. Deep learning algorithms designed for glioblastoma multiforme surgeries showcase the potential for simultaneous maximization of tumor removal and preservation of healthy tissue, a concept applicable to challenging intramedullary spinal cord tumors like astrocytoma's.

Intraoperative decision-making benefits from machine learning applications, as seen in Khalsa SS et al.'s study using Raman scattering and convolutional neural networks to identify brain tumors with high diagnostic accuracy. Automated models capable of providing rapid and accurate preliminary diagnoses during surgery address challenges associated with artifacts and variability in intraoperative specimen preparation. This innovation facilitates informed decision-making, guides treatment options, and informs prognosis in real-time.

Navigation and robotics in modern spine surgery are promising areas for machine learning integration. Predictive algorithms using real-world data can streamline preoperative planning, reducing the time spent by surgeons preparing for surgeries. Three-dimensional convolutional neural networks prove valuable in stereotactic radiation therapy planning, while machine learning aids in automatic segmentation and contouring of tumors, optimizing treatment plans based on individual patient and tumor characteristics. Computer-assisted navigation and intraoperative surgical robotics, enriched with artificial intelligence features, hold the potential to enhance precision, efficiency, and safety, ultimately serving as valuable tools for surgeons in the operative room. Despite their potential to increase efficiency, these technologies remain supportive tools, with the primary decision-maker remaining the skilled surgeon.

IV. Results

The integration of artificial intelligence (AI) into the realm of spine surgery has increasingly focused on predicting outcomes and prognosis, offering valuable insights for informed decision-making and personalized patient management. Early attempts in spine surgery have laid the foundation for more advanced machine learning models. While AI applications in spinal deformity surgery have been explored, the development of precise predictive models for spinal tumors remains somewhat limited.

In the specific context of spinal tumors, the rarity of such cases has contributed to a scarcity of literature consolidating diverse predictors into integrated risk models. Currently, the only published predictive machine learning model for spinal tumors, by Jin et al., utilized a least absolute shrinkage and selection operator (LASSO) approach to predict post-resection outcomes for intradural tumors. Their algorithm, incorporating patient-specific and tumor-specific factors, outperformed other models, showcasing superior discrimination and accuracy in predicting non-home discharge and 90-day readmissions following surgery for intradural tumors. While non-machine learning calculators have also shown promise in risk stratification for patients undergoing spinal surgery, robust machine learning models are yet to be established, marking a promising pathway towards achieving personalized care for spinal cord tumors.

While convolutional neural networks (CNNs) and comparative procedures have demonstrated strong in their capacity to recognize many-sided designs, the inborn "discovery" nature of these models raises worries about interpretability. The robotized idea of brain networks permits them to uncover designs that might escape human eyewitnesses, yet it leaves specialists with restricted understanding into the basic reasoning for the distinguished examples. It is essential to acknowledge that the quality of the training data is critical to the effectiveness of AI algorithms. Many exploration attempts depend on moderately little datasets, presenting the potential for foundational and determination inclinations inside the information, which can impact the relationships and expectations created by the models.

In the mix of computerized reasoning into a medical procedure, moral and lawful contemplations should be painstakingly tended to. Issues like patient security, classification, and assurance from cybercrime become central. The administrative scene, both medicolegally and morally, requires consistent refreshing and unequivocal definition, as considering a calculation or its designers responsible in case of an unfriendly result can present difficulties. To guarantee their generalizability in clinical settings, machine learning models should undergo rigorous retrospective analysis and external validation. Starting limited scope planned executions, much the same as stages 1 and 2 of clinical preliminaries, becomes fundamental. These executions not just permit specialists to grasp what these calculations mean for decision-production at a singular level yet additionally empower a comprehension of their belongings across assorted populaces. Before widespread implementation in clinical practice, this multifaceted strategy ensures a thorough comprehension of the implications, limitations, and potential advantages.

Looking beyond spinal tumors, predictive models developed for spine surgery outcomes and complications provide valuable insights. Lee et al. created a surgical site infection calculator, demonstrating fair predictive power, while other models predict the likelihood of needing single versus multiple operative debridements after surgical site infection occurrence. Additionally, an AI preoperative algorithm has been designed to predict the risk and automatically detect intraoperative vascular injury during lumbar surgery, highlighting the potential of machine learning in informing decision-making and shaping patient management. Despite these advancements, further exploration and validation of these models in the context of spine surgery are needed to assess their clinical utility.

Moreover, the realm of potential imaging biomarkers, particularly within magnetic resonance imaging, adds another layer to predicting outcomes in spinal disorders. These biomarkers, in conjunction with clinical data, hold the potential to improve prognostic accuracy and inform treatment decisions. For instance, identifying molecular and genetic profiles, such as platelet-derived growth factor in spinal ependymomas, could unveil treatment targets and enhance treatment options for improved patient outcomes. However, challenges persist, as contradictory evidence suggests that the predictive value of molecular profiles may be influenced by tumor location, hindering the development of machine learning models based on molecular data. The nuanced nature of genetic variants and histologic grades in spinal tumors warrants further exploration to unlock the full potential of AI in enhancing prognostic accuracy and treatment strategies for patients with spinal disorders.

V. Conclusion

A Artificial intelligence (AI) coupled with promising machine learning (ML) techniques well known from computer science is broadly affecting many aspects of various fields including science and technology, industry, and even our day-to-day life. The future holds the potential for perceptive models that consistently coordinate radiographic, pathologic, and oncologic information, offering more exact, and unprejudiced evaluations of endurance rates and the feasibility of interventions. These inventive models must go through intensive approval processes and thorough quality evaluations to guarantee their security and viability when converted into clinical practice. This cooperative methodology empowers the opening of the maximum capability of artificial intelligence, making ready for a progress to a period of information driven customized medication in the region of spinal cord tumors.

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