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Research on Classification Diagnosis and Treatment of Gliomas Based on Multimodal MRI and Artificial Intelligence Assisted Decision making

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ABSTRACT

Glioma is the most common type of primary intracranial malignant tumor; The highly heterogeneous and aggressive characteristics pose great challenges to the diagnosis and treatment of patients. Accurate preoperative grading, molecular typing prediction, and personalized treatment are of great significance in improving patient survival time and prognosis. With the development of multimodal magnetic resonance imaging technology, it can reflect the pathological and physiological characteristics of tumors from multiple angles and in all directions, including changes in morphology, function, and metabolism. At the same time, with the development of artificial intelligence, especially machine learning and deep learning, powerful technical means have been provided for mining deep level information from image big data and establishing objective quantitative analysis models. This article introduces the methods of using various MRI data for characteristic analysis of gliomas, and presents the process of constructing an artificial intelligence assisted diagnostic model, including image data preprocessing, tumor segmentation, feature extraction and screening, grading diagnosis, and molecular typing prediction model design and validation. Finally, the support of artificial intelligence assisted decision support systems for clinical diagnosis and treatment was discussed, including preoperative planning, prognosis assessment, efficacy evaluation, and AI visualization assisted decision support in multidisciplinary consultations; The combination of multimodal imaging and artificial intelligence is expected to promote the transformation of glioma from imaging diagnosis to diagnosis and treatment decision-making, and promote the development of its grading diagnosis and treatment model.

KEYWORDS

Glioma; Multi modal magnetic resonance imaging; Artificial intelligence; Radiomics; Deep learning; Decision support

1. INTRODUCTION

Gliomas are the most common primary tumors of the nervous system, classified as grades I-IV according to WHO. Grades III-IV gliomas are characterized by high malignancy, rapid progression, and poor prognosis. There are significant differences in treatment plans at different levels, so preoperative determination of tumor grade and molecular level is of great significance for guiding treatment. MRI is the main method for the diagnosis and treatment of glioma. Conventional sequence (T1/T2/FLAIR) displays tumor morphology and range; Enhancing T1 reflects the degree of destruction of the tumor BBB.

But its evaluation of microstructure and biological behavior is insufficient. The development of multimodal MRI (DWI, DTI, PWI, MRS, etc.) has made the information related to water molecule dispersion, blood flow perfusion, and metabolic concentration very rich. In the face of such a massive

amount of data, the traditional manual interpretation method has problems such as being too subjective and unable to obtain high sensitivity; AI technology can automatically learn imaging patterns, obtain diagnostic and prognostic indicators, and provide reference evidence for clinical diagnosis and treatment. The author intends to review the research on AI assisted diagnosis and treatment of glioma based on multimodal MRI, in order to understand its clinical application prospects.

2. CURRENT STATUS AND CHALLENGES OF PRECISION DIAGNOSIS AND TREATMENT OF GLIOMA

At present, the main treatment methods for glioma are surgery combined with radiotherapy, chemotherapy, and targeted therapy [1]. The extent of surgical resection is crucial for the prognosis of patients; However, due to the invasive nature and location in the functional area of gliomas, complete resection is difficult. Postoperative pathological examination is an important basis for determining subsequent treatment strategies. Molecular level testing was listed as an important part in the fifth edition of WHO, and molecular information was added as a classification criterion in the fourth edition in 2016. IDH mutations and 1p/19q combined deletions are mandatory test items. There are significant differences in prognosis and treatment sensitivity among different molecular subtypes.

At present, molecular information relies on surgical or biopsy acquisition, which leads to sampling errors, inability to fully reflect tumor heterogeneity, and difficulty in biopsy for tumors in deep or high-risk areas. Therefore, there is an urgent need for clinical provision of a non-invasive, reusable, and comprehensive way to evaluate tumor heterogeneity [2]. Multimodal MRI can reflect the biological characteristics of tumors from multiple levels, such as DWI reflecting cell density, PWI reflecting angiogenesis, and MRS reflecting metabolic activity. The combination of multimodal imaging and AI can predict tumor grade and molecular features, and perform non-invasive testing on patients before surgery, thus supplementing the limitations of other methods.

However, the differences in equipment and scanning parameters among different institutions, as well as the standardization challenges in image interpretation, remain the current challenges.

3. ANALYSIS OF GLIOMA FEATURES BASED ON MULTIMODAL MRI

Multimodal MRI reveals the pathological and physiological status of tumors from different perspectives:

Conventional sequence: T1 enhancement reflects the integrity of the blood-brain barrier (high-grade gliomas often exhibit uneven enhancement); T2/FLAIR shows edema and infiltration range.

Diffusion weighted imaging (DWI/DTI): ADC values reflect cell density (high-grade gliomas have higher cell density and lower ADC values); DTI can track white matter fiber bundles and evaluate the relationship between tumors and important pathways [3].

Perfusional imaging (DSC/DCE/ASL): Reflecting tumor hemodynamics. High grade gliomas have abundant neovascularization and usually elevated rCBV, which is an effective indicator for distinguishing grades and differentiating recurrence from radiation necrosis.

Magnetic resonance spectroscopy (MRS): detects metabolite concentrations. When tumor proliferation is active, the Cho peak increases, and when neurons are damaged, the NAA peak decreases. The appearance of the Lip peak indicates necrosis.

Combining information from multiple different modalities for analysis can better evaluate the characteristics of tumors, such as the enhanced area representing the disruption of the blood-brain barrier, but the extent of infiltration is often greater than that of the enhanced area; High grade gliomas often have high perfusion and limited diffusion at the edge of enhancement. Multimodal features are

also related to molecular subtyping (such as IDH mutation type), which can help us achieve non-invasive preoperative diagnosis of tumors.

4. CONSTRUCTION AND APPLICATION OF ARTIFICIAL INTELLIGENCE ASSISTED DIAGNOSTIC MODELS

Developing an AI assisted diagnostic model is a comprehensive process that includes multiple key steps from raw data to clinical implementation, including data preprocessing, tumor segmentation, feature calculation and modeling, model training and testing. The selection and quality control of each step will affect the quality of the final model.

4.1. Image Data Preprocessing and Segmentation of Tumor Regions of Interest

Due to differences in equipment, parameters, and patient movements, raw MRI data may vary and require standardized preprocessing, such as image format conversion, skull removal, bias field correction, registration, and resampling. The most critical part is the registration process between multiple modalities, which uses rigid or nonlinear methods to align the images of each sequence in the same space, ensuring that they have the same anatomical position[4]. For regions of interest in tumors, segmentation is the most important task. Glioma subregions (enhanced tumors, non enhanced tumors, necrosis, edema) should be segmented separately for fine analysis.

Traditional manual segmentation is subjective and time-consuming. U-Net and its derivative versions based on deep learning utilize encoder decoder architecture and skip connections to achieve pixel level classification of images, and 3D convolutional neural networks can directly input voxel data to improve segmentation accuracy; The BraTS Challenge has promoted the development of related algorithms. Currently, the proposed models are close to human level in public datasets, but lack sufficient cross center generalization ability. Transfer learning and domain adaptation can be used to improve this.

4.2. Extraction and Dimensionality Reduction Screening of Radiomics Features

Imaging omics conducts massive quantitative feature mining on tumor targets, obtaining shape (volume, area, sphericity), first-order moments (mean, kurtosis, skewness), and texture features (gray level co-occurrence matrix, gray level run length matrix, etc.) to describe the geometric structure, gray level distribution, and heterogeneity of tumors; Wavelet transform can capture multi-scale information. The low-frequency profile corresponds to biological behavior. There are often thousands of feature dimensions, and redundancy and noise can easily lead to overfitting in the model, so dimensionality reduction filtering is necessary.

The main methods used are variance to remove low variance features, correlation matrix to merge strongly correlated features together, univariate hypothesis testing to remove non significant features, or Lasso regression, random forest and other feature selection algorithms for supervised feature selection, while minimizing the penalty term for feature selection [5].

4.3. Construction of Hierarchical Diagnosis Model Based on Machine Learning

Based on multimodal image features, gliomas can be graded, and machine learning algorithms can be used to objectively quantify these features. After feature filtering, we can use LR to achieve better interpretability, SVM can handle higher dimensional data and perform well in small datasets, RF to some extent prevents overfitting and can also be used to calculate the importance of various features, while XGBoost and LightGBM are high-precision ensemble methods. Finally, we can verify the effectiveness of our model through cross validation and a separate test set. Using commonly used accuracy, sensitivity, specificity, and area under the ROC curve [6]. Multi sequence fusion is superior

to single sequence fusion, and perfusion and diffusion parameters make significant contributions. The ranking of feature importance can indicate information such as texture entropy and surface area volume ratio reflecting tumor heterogeneity and grade, which helps to improve the interpretability of the model.

4.4. Tumor Grading and Molecular Typing Prediction Based on Deep Learning

Deep learning extracts hierarchical features directly from raw images through an end-to-end learning mode, avoiding the hassle of manual feature engineering. Convolutional neural networks are the most commonly used method for image data. Two dimensional or three-dimensional convolutional neural networks can be used to classify multimodal MRI in glioma grading. Two dimensional networks have fast computing speed, but may lose spatial information between layers; 3D networks can fully utilize the context in 3D space, but they require higher computational resources. Common backbone networks include ResNet, DenseNet, etc. Their residual connections and dense connections make it possible to train deeper networks.

How to integrate information from multiple modalities will have a significant impact on the final model. Early fusion inputs images of different modalities as different channels into the entire network, which is a simple method but requires accurate registration between each modality. Middle fusion uses different subnets to obtain the features of each modality and then fuses them, which can better preserve the characteristics of each modality. Late fusion combines the classification results obtained from each modality in the final step. In addition, adding an attention module can also improve the model's performance [7]. Spatial attention allows the network to focus more on the tumor part, while channel attention adaptively weights different feature channels.

In recent years, Transformer architecture has shown excellent performance in visual tasks due to its powerful global relationship modeling ability, and has also begun to be applied in multimodal MRI analysis.

Molecular subtyping prediction is of great significance for the precise diagnosis and treatment of gliomas. The IDH gene mutation and 1p/19q co deletion are currently the most important molecular classification indicators for gliomas. Previous studies have found that combining deep learning methods with radiomics can assist in predicting the molecular subtypes of IDH and 1p/19q. IDH mutant tumors often exhibit T2-FLAIR mismatch, clear boundaries, and less enhancement. And deep learning methods can capture these subtle phenotypic differences, making them highly accurate in prediction.

In contrast, predicting images in the 1p/19q state is more difficult and has lower accuracy than predicting IDH, which may be related to the weaker relationship between its image presentation and gene phenotype. In summary, it is believed that by fusing multi-source data and applying more advanced deep learning algorithms, prediction accuracy can be improved [8].

4.5. Model Performance Evaluation and Clinical Validation

After establishing a good model, it must undergo sufficient evaluation and validation before considering whether the model has clinical application value. Internal validation is the use of data from the same center for cross validation or leaving a validation set to evaluate the preliminary model performance. External validation is the use of data from other centers and manufacturers for independent validation, which is the most reliable standard for measuring the generalization and robustness of a model. Therefore, the difference in generalization of the model to external data directly affects whether the model can be applied and promoted in practical production and life [9].

The selection of indicators should be based on clinical significance. For the task of grading diagnosis, the main focus is on whether the model can effectively distinguish between high-grade and low-grade tumors, with the area under the ROC curve being the most critical indicator; For the prediction of

molecular typing, due to the fact that there are often fewer positive samples, attention needs to be paid to sensitivity, specificity, and the trade-off F1 score between the two; In addition, the calibration curve can measure the degree of consistency between the predicted probability value of the model and the actual probability of occurrence. Decision curve analysis can quantify the net benefits of the model on clinical decision-making at different threshold levels.

Finally, it is necessary to compare the performance of the model with existing clinical standards, such as comparing the accuracy of the model's diagnosis with the results of radiologists with different years of experience, to determine whether the model helps to improve the diagnostic level or reduce the quality difference among observers. Prospective trials are the final hurdle in testing the clinical value of a model, but there are currently few relevant reports and they will be the focus of future research. Finally, the interpretability and transparency of the model affect the level of trust and acceptability of clinical physicians towards it.

For deep learning, a type of "black box" model, the focus of the model's judgment process can be visualized through methods such as class activation maps to confirm whether these positions are clinically recognized, which is crucial for the clinical implementation of the model.

5. CLINICAL INTEGRATION OF ARTIFICIAL INTELLIGENCE ASSISTED DECISION SUPPORT SYSTEM

Integrating artificial intelligence models into clinical workflows and building auxiliary decision support systems is the ultimate way to unleash their value. The system should have a user-friendly interface and be integrated with hospital information systems and imaging archiving and communication systems to achieve automatic data acquisition and analysis.

5.1. Preoperative Non-Invasive Grading and Surgical Planning Assisted Decision-Making

Determining the preoperative tumor grade is an important factor in guiding surgery. High grade gliomas emphasize maximum resection, while low-grade gliomas can be removed within functional limits. AI models can provide objective grading results to assist neurosurgeons in making decisions.

The relationship between tumors and important functional areas is the core of surgical planning. Diffuse tension imaging fiber bundle tracing can display corticospinal tract, arcuate tract, etc. Artificial intelligence can automatically segment fiber bundles and quantify the distance between tumors and fiber bundles. Functional magnetic resonance imaging can locate the motor and language cortex, and understand the location of functional areas before surgery, which is beneficial for protecting functional areas during surgery. By integrating information from image segmentation, grading prediction, and functional localization, a three-dimensional visualization model can be established to vividly display the tumor and important surrounding anatomical structures, guiding doctors to choose appropriate surgical approaches and predict resection risks [10].

5.2. Imaging Associations and Prognostic Prediction of Molecular Pathological Subtypes

Molecular typing has a guiding role in prognosis and treatment plan selection. IDH mutant gliomas have a long survival time, partial resection is sufficient, and the prognosis is good; However, IDH wild-type glioblastoma is highly invasive and requires active treatment. The prediction of preoperative molecular typing can provide a preliminary understanding of the patient's prognosis and provide a reference for the patient and their family. The study on the correlation between imaging features and molecular typing indicates that imaging can serve as an alternative biomarker for

molecular typing. For example, IDH mutant tumors often exhibit T2-FLAIR mismatch, high apparent diffusion coefficient values, and low perfusion.

Conduct correlation analysis based on multimodal features and molecular typing, and apply it to imaging molecular modeling to achieve non-invasive molecular typing; Simultaneously combining clinical variables such as patient age, KPS score, and other information, a personal prognostic evaluation system is developed to estimate the patient's survival time and develop corresponding follow-up strategies.

5.3. Evaluation of Treatment Response and Differentiation of Pseudo Progression

Imaging follow-up after glioma surgery and radiotherapy/chemotherapy is very important, but treatment-related changes such as pseudoprogression and radiation necrosis are difficult to distinguish from true tumor progression on conventional MRI, both of which are characterized by increased enhancement and edema. Often, further treatment is delayed due to the inability to distinguish. The application of multimodal MRI can assist in differentiation. True progression of tumors is usually characterized by high perfusion and low apparent diffusion coefficient values. The choline peak increases. Pseudo progression and radiation necrosis are hypoperfusion and may have lipid peaks. AI models can integrate multimodal information to increase the accuracy of identification. The dynamic monitoring model can observe the characteristics of lesion changes and detect signs of progression through continuous image changes.

5.4. Visualized Decision Support Process in Multidisciplinary Diagnosis and Treatment

Multidisciplinary diagnosis and treatment is the standard model for glioma diagnosis and treatment. Neurosurgery, imaging, pathology, radiotherapy, and oncology physicians discuss and develop individualized plans together. Artificial intelligence assisted decision-making systems can provide visual support for interdisciplinary discussions. The system interface can integrate patient clinical information, multimodal imaging, and artificial intelligence prediction results. Display automatic tumor segmentation results and 3D reconstruction, display grading probability and molecular typing prediction, label functional areas and fiber bundles. During the discussion, parameters can be dynamically adjusted to view simulation results of different treatment plans.

This visual aid can help multidisciplinary doctors reach consensus, accelerate decision-making speed, and make it more scientific. The system can also provide patients with information about their tumor status and treatment plans, thereby helping them understand their illness and increasing their compliance.

6. CONCLUSION

The research on artificial intelligence assisted decision-making in multimodal MRI is a new approach for precise diagnosis and treatment of glioma. It utilizes multimodal information such as diffusion, perfusion, and spectroscopy, as well as machine learning and deep learning algorithms for preoperative non-invasive grading, molecular typing prediction, prognosis, and treatment response monitoring, to assist clinical decision-making. Artificial intelligence models can explore the deep features of images, overcome the limitations of the human eye, and promote the transformation of imaging from qualitative to quantitative. At present, the relevant work still needs to be further deepened. In terms of data, there is a lack of representative multi center, large-scale, and homogeneous datasets, and a general model still needs to be improved.

At the algorithmic level, the model is opaque and lacks sufficient clinical credibility; At the level of transformation, there is still a long way to go from scientific research to clinical practice. Conducting

prospective research in this field to verify its practical clinical significance and how to better integrate it with clinical workflows are urgent issues that need to be addressed. I believe that in the future, with the development of imaging technology and algorithms, the combination of multimodal MRI and artificial intelligence will become even closer. The discovery of gene image correlation in imaging genomics, combined with digital pathology and imaging, and dynamic modeling of longitudinal data will push the diagnosis and treatment of glioma to new heights.

Through cross collaboration between medical and engineering departments, a clinically applicable auxiliary decision-making system is expected to achieve intelligent, precise, and personalized grading and diagnosis of glioma, ultimately improving patient prognosis.

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