**Title:** Brain Tumor Segmentation and Survival Prediction using Deep Neural Networks

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**Abstract:**

The project focuses on the vital task of brain tumor segmentation in MRI images to facilitate survival prediction among patients undergoing treatment. Leveraging methodologies derived from seminal works ([1], [2], [3]), the implementation, crafted using the Keras module within the TensorFlow framework in Python, is publicly available in the provided [GitHub repository](https://github.com/shalabh147/Brain-Tumor-Segmentation-and-Survival-Prediction-using-Deep-Neural-Networks). This research aims to streamline the cumbersome and subjective manual segmentation process by automating the classification of tumor and non-tumor regions in brain scans. The segmentation results not only aid in diagnosing the volume, shape, and localization of brain tumors but also form the basis for predicting patient survival rates based solely on MRI images.

**Introduction:**

Brain tumor segmentation plays a pivotal role in diagnostic procedures, offering crucial insights into tumor characteristics and behavior. While manual segmentation is labor-intensive and prone to subjective interpretations, automated segmentation presents an attractive solution, promising quicker and potentially more accurate tumor parameter descriptions. The objective of this research is to detect and segment various parts of the brain by active tumorous tissue, necrotic regions, and edema, crucial for precise diagnosis and patient monitoring. The correlation between segmentation outcomes and patient survival rates motivates this research's integrated approach.

**Technical Approach & Models:**

The study employs a meticulous technical approach centered around the implementation of sophisticated deep neural network architectures for the precise segmentation of brain tumors in MRI images. This methodology is enriched by the utilization of a diverse and comprehensive dataset encompassing varying grades of gliomas.

1. **Brain Tumor Segmentation Models:** The crux of the research involves the development and meticulous evaluation of cutting-edge models customized for brain tumor segmentation within the context of the BraTS 2018 dataset:

·   **High Grade Glioma (HGG):** The primary focus rests on the development of models adept at accurately delineating high-grade gliomas. These models undergo rigorous training, validation, and testing on a meticulously curated subset of MRI images predominantly representing high-grade gliomas.

·   **Low Grade Glioma (LGG):** While not the primary focus, the research might explore and analyze models trained on MRI images depicting low-grade gliomas. These models serve supplementary roles for comparative analysis, validation, or targeted experimentation to contrast with high-grade glioma models.

2. **Patient Dataset Utilization**: A pivotal aspect of the study involves harnessing a diverse and expansive patient dataset:

·   **HGG Patients:** Central to the research, this dataset comprises a substantial cohort diagnosed with high-grade gliomas. The MRI images from these patients serve as foundational elements for training and evaluating the efficacy of brain tumor segmentation and survival prediction models.

·   **LGG Patients:** In addition to the primary focus on high-grade gliomas, the research might integrate data from patients diagnosed with low-grade gliomas. This inclusion facilitates comparative analysis and exploration of specific nuances related to different tumor grades, enriching the depth of the study.

This meticulous and inclusive approach, encompassing a variety of glioma grades within both the models and the patient dataset, aims to cultivate robust neural network architectures adept at precise brain tumor segmentation and survival prediction.

**Experiments & Results:**

The research undertakes an extensive series of experiments, deploying meticulously crafted neural network architectures on the BraTS 2018 dataset to evaluate their efficacy in brain tumor segmentation and survival prediction.

The study highlights a significant aspect of the BraTS dataset, noting its challenge with extreme class imbalance. To address this, potential solutions involve implementing a Multi-Class Soft-Dice loss, employing Class Weights Utility with varying weights to penalize incorrect labels, and training 2D models exclusively on slices containing pixels from all classes.

**1.** **Model Training and Evaluation:**

·   **UNet 3D and VNet 3D Performance:** The study rigorously trains and evaluates both UNet 3D and VNet 3D architectures for brain tumor segmentation. Extensive experiments are conducted, detailing the nuances of training procedures, parameter tuning, and validation strategies employed for these models. Comprehensive evaluations measure the segmentation accuracy, sensitivity, and specificity across various tumor classes, providing a detailed analysis of their performance.

·   **Integration of 2D UNets along Axes:** Delving deeper, the research explores the integration of 2D UNet architectures along different axes to enhance segmentation efficiency. Detailed experimentation is conducted, focusing on the fusion of segmentation results and the subsequent evaluation across different tumor classes and imaging planes.

**2.** **Survival Prediction Network Evaluation:**

·   **Architecture and Predictive Performance:** The study outlines a survival prediction network architecture inspired by prior works. It thoroughly explores the correlation between segmented images and survival prediction. The experiments gauge the accuracy and predictive power of the network, detailing the classification and regression models' performance in predicting survival ranges and days, respectively.

**3.** **Comparative Analysis and State-of-the-Art Comparison:**

·   **Benchmarking against State-of-the-Art Models:** The research benchmarks its models against state-of-the-art methodologies in brain tumor segmentation and survival prediction. Comparative analyses highlight the strengths and limitations of the proposed models concerning existing benchmarks, showcasing their advancements and potential improvements.

·   **Algorithmic Contributions:** The paper meticulously elucidates the algorithms utilized within the models and their comparative performance, showcasing the novel contributions and the areas where the proposed methodologies excel or present opportunities for further enhancements.

Through extensive experimentation and meticulous analysis, the study not only presents its findings but also offers comprehensive insights into the strengths, limitations, and potential advancements within the domain of brain tumor segmentation and survival prediction using deep neural networks.

**Conclusion:**

This research advances the field of brain tumor segmentation and survival prediction using deep neural networks. This study’s findings, although promising, underscore the need for continued exploration and innovation in this domain. Future work might involve deploying more sophisticated architectures and amalgamating clinical and radiomic features with segmentation-derived information for more comprehensive survival predictions.

References:

[1] Fabian Isensee et al. "Brain tumor segmentation and radiomics survival prediction: Contribution to the BRATS 2017 challenge."

[2] Fausto Milletari et al. "V-net: Fully convolutional neural networks for volumetric medical image segmentation."

[3] Xiaomei Zhao et al. "3d brain tumor segmentation through integrating multiple 2d fcnns."