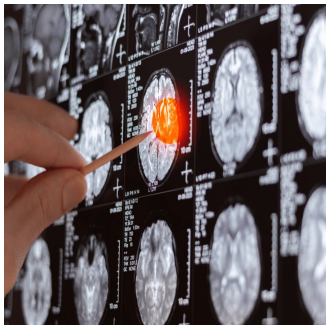
Dynamic AI Framework Enhances Brain Tumour Segmentation



Accurate brain tumour identification and segmentation are critical for early diagnosis, tailored treatment and improved survival outcomes. However, structural variability of tumors makes automated detection complex. Researchers from Khulna University of Engineering and Technology have developed a dynamic segmentation network (DSNet), a deep learning framework combining dynamic convolution, adversarial learning and attention mechanisms. The model enhances precision in three-dimensional magnetic resonance imaging (MRI) analysis and extends to survival prediction, providing an integrated clinical tool for diagnosis and prognosis.

Integrating Deep Learning for Brain Tumour Detection

Traditional manual segmentation is labour-intensive and dependent on expert interpretation. Automated techniques, particularly those using convolutional neural networks (CNNs), have gained prominence for their ability to identify tumours more consistently. DSNet builds on this progress by addressing key limitations in existing CNNs, such as their difficulty in handling fine-grained tumour boundaries and spatial heterogeneity. The framework employs dynamic convolutional filters that adapt to tumour-specific variations, improving segmentation across diverse MRI modalities including T1, T1ce, T2 and FLAIR. These modalities collectively capture critical diagnostic information, such as tissue differentiation, tumour borders and fluid distribution, enhancing clinical interpretability.

The study's primary dataset, BraTS 2020, served for training, with BraTS 2019 and 2018 used to evaluate generalisability. DSNet's integration of adversarial learning strengthens segmentation boundaries by introducing a critic network that refines outputs through competitive feedback, leading to more realistic segmentation results. The system's architecture also includes attention-based skip connections, enabling the network to focus on tumour-relevant regions during feature reconstruction. This multi-component structure provides a significant advance over conventional U-Net-based models, which rely on static convolution and lack adaptive contextual awareness.

Achieving State-of-the-Art Segmentation Accuracy

The DSNet model was evaluated using established metrics, including the Dice Similarity Coefficient (DSC), Intersection over Union (IoU) and sensitivity. These indicators measure alignment between predicted and ground truth tumour regions. The five-stage DSNet configuration achieved optimal performance, balancing accuracy with computational efficiency. Using the BraTS 2020 dataset, DSNet reached Dice scores of 0.959 for whole tumours, 0.975 for tumour cores and 0.947 for enhancing tumours. Comparable results were achieved when validated on BraTS 2019 and 2018, confirming strong generalisation across datasets.

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Compared with leading architectures such as U-Net, Attention U-Net, Res U-Net and Transformer-based models like TransBTS and SwinBTS, DSNet consistently demonstrated higher accuracy. Its dynamic convolution mechanism and adversarial learning component contributed to superior boundary delineation, especially in complex tumour regions. The network's resilience was further validated through cross-dataset testing, where it maintained high performance without retraining, underscoring robustness in varied imaging conditions. Ablation studies confirmed that the inclusion of dynamic convolution, attention mechanisms and critic networks each progressively enhanced segmentation accuracy.

Extending to Survival Prediction and Clinical Utility

Beyond segmentation, DSNet incorporates a survival prediction module using volumetric and clinical data. By quantifying segmented tumour volumes and integrating patient age, the system classifies survival into short-, medium- and long-term categories. Among several tested algorithms, the Random Forest classifier achieved the most reliable validation accuracy. Additional evaluation using a deep neural adaptation of the Cox proportional hazards model, DeepSurv, supported the framework's prognostic capabilities. The use of Shapley Additive Explanations (SHAP) provided interpretability, showing that age and tumour volume were the most influential predictors of survival, aligning with established clinical understanding.

A web-based application was developed to facilitate real-world application of the model. The interface enables clinicians to upload MRI scans, receive segmentation masks and generate survival predictions within 40 seconds. Built for local deployment, the system ensures compliance with data protection standards and is available as an open-source research prototype. This implementation demonstrates DSNet's potential for practical clinical integration, bridging the gap between research models and clinical workflow tools.

DSNet represents a significant advancement in automated 3D brain tumour analysis, combining dynamic convolution, attention mechanisms and adversarial learning to deliver precise segmentation and integrated survival prediction. Validated across multiple benchmark datasets, the model surpasses existing architectures in accuracy and robustness while remaining computationally efficient. The inclusion of a user-friendly web application extends its accessibility to healthcare professionals, supporting faster and more consistent clinical decision-making. By uniting advanced deep learning methods with interpretability and workflow integration, DSNet demonstrates strong potential for improving diagnostic precision and patient prognosis in neuro-oncology.

Source: Healthcare Analytics

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