**Brain Tumour Image Segmentation Using Deep Networks**

summarize the text :

Accurate segmentation of tumours through medical images is of particular importance as it provides information essential for analysis and diagnosis of cancer as well as for mapping out treatment options and monitoring the progression of the disease. Brain tumours are one of the fatal cancers worldwide and are categorised, depending upon their origin, into primary and secondary tumour types [1]. The most common histological form of primary brain cancer is the glioma, which originates from the brain glial cells [2] and attributes towards 80% of all malignant brain tumours [3]. Gliomas can be of the slow-progressing low-grade (LGG) subtype with a better patient prognosis or are the more aggressive and infiltrative high-grade glioma (HGG) or glioblastoma, which require immediate treatment [4]. These tumours are associated with substantial morbidity, where the median survival for a patient with glioblastoma is only about 14 months with a 5-year survival rate near zero despite maximal surgical and medical therapy [5]. A timely diagnosis, therefore, becomes imperative for effective treatment of the patients. Magnetic Resonance Imaging (MRI) is a preferred technique widely employed by radiologists for the evaluation and assessment of brain tumours [1]. It provides several complimentary 3D MRI modalities acquired based on the degree of excitation and repetition times, i.e. T1-weighted, post-contrast T1-weighted (T1ce), T2-weighted and Fluid-Attenuated Inversion Recovery (FLAIR). The highlighted subregions of the tumour across different intensities of these sequences [6], such as the whole tumour (the entire tumour inclusive of infiltrative oedema), is more prominent in FLAIR and T2 modalities. In contrast, T1 and T1ce images show the tumour core exclusive of peritumoural oedema [7]. It allows for the combinative use of these scans and the complementary information they deliver towards the detection of different tumour subregions. The Multimodal Brain Tumour Segmentation Challenge (BraTS) is a platform to evaluate the development of machine learning models for the task of tumour segmentation, by facilitating the participants with an extensive dataset of 3D MRI images of the gliomas (both LGG and HGG) and associated ground truths annotated by expert physicians. The provided multimodal scans are used for both training and validating the neural networks designed for the particular segmentation task [6], [8]–[11]. Manually delineating brain tumour subregions from MRI scans is a subjective task, and therefore it is time-consuming and prone to variability [12]. Automated segmentation of gliomas from multimodal MRI images can consequently assist the physicians to speed-up diagnosis and surgical planning as well as provide an accurate, reproducible solution for further tumour analysis and monitoring [13], [14]. The classical methods of automated brain tumour segmentation rely on feature engineering, which involves the extraction of handcrafted features from input images with follow-up training of classifier [11], [15]. Unsupervised learning algorithms bypass the complexity in designing and selecting features by automatically learning a hierarchy of feature representations [16]–[19], with deep learning models excelling at the task [11]. Convolutional Neural Networks (CNNs) is regarded as the state of the art methods for brain tumour image segmentation as they learn the most useful and relevant features automatically [6]. However, accurate segmentation of tumour remains a challenge; due to heterogeneity in terms of shape, size, and appearance of the gliomas as well as ambiguous and fuzzy boundary existing between cancer and brain tissue [20]. The intensity variability of the MRI data further adds to this difficulty [13]. Therefore, it is still open to improvement, allowing further exploration for better segmentation techniques and accuracy. In this work, we utilise multiple 3D CNN models for brain tumour segmentation from multimodal MRI scans and ensemble their probability maps for more stable predictions. The networks are trained separately, with hyperparameters optimised for each model, on the training dataset acquired from the 2019 Brain Tumour Segmentation (BraTS) challenge. A rigorous evaluation on the BraTS validation set resulted with the proposed ensemble achieving dice scores of 0.750, 0.906 and 0.846 for enhancing tumour, whole tumour, and tumour core, respectively.

**Result**

Accurate segmentation of brain tumours through medical images is crucial for analysis, diagnosis, treatment, and monitoring the disease. Magnetic Resonance Imaging (MRI) is widely used for brain tumour assessment, and the Multimodal Brain Tumour Segmentation Challenge (BraTS) provides a dataset of 3D MRI images of gliomas for machine learning models' development. Convolutional Neural Networks (CNNs) are state-of-the-art methods for brain tumour segmentation, but accurate segmentation remains challenging due to tumour heterogeneity and ambiguous boundaries between cancer and brain tissue. In this work, multiple 3D CNN models are utilised and ensembled their probability maps for more stable predictions, achieving good results in the BraTS validation set.

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Automated segmentation of gliomas from multimodal MRI images can speed up the diagnosis and surgical planning and provide accurate and reproducible solutions for further tumour analysis and monitoring. The traditional automated segmentation methods rely on feature engineering, which involves extracting handcrafted features from input images with follow-up training of classifiers, while unsupervised learning algorithms automatically learn a hierarchy of feature representations. Deep learning models, particularly CNNs, excel at tumour image segmentation as they learn the most useful and relevant features automatically. However, there are still challenges in accurate tumour segmentation due to the heterogeneity in tumour shape, size, and appearance and the intensity variability of the MRI data. Further exploration for better segmentation techniques and accuracy is still open to improvement.

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The proposed method in this work utilises multiple 3D CNN models trained separately with hyperparameters optimised for each model, and their probability maps are ensembled for more stable predictions. The evaluation on the BraTS validation set showed that the proposed ensemble achieved good results with dice scores of 0.750, 0.906, and 0.846 for enhancing tumour, whole tumour, and tumour core, respectively. Such results demonstrate the potential of this method to improve the accuracy of tumour segmentation and help physicians with diagnosis and treatment planning. Further research can explore the use of other deep learning models or novel approaches to improve the segmentation of brain tumours.

The utilisation of deep learning models and machine learning techniques in medical image analysis is a rapidly growing area of research. The segmentation of brain tumours is just one application of these techniques in medical imaging. Other applications include the detection of breast cancer, lung cancer, and liver diseases, among others. The use of these techniques can improve the accuracy of medical diagnoses, reduce the time required for detection and treatment, and ultimately improve patient outcomes.

However, the adoption of these techniques in clinical practice also presents several challenges. One of the most significant challenges is the need for validation and regulation of these techniques. The use of deep learning and machine learning models in medical image analysis requires appropriate validation and assessment to ensure their safety, reliability, and generalisability across different patient populations.

Overall, the proposed method in this work provides a promising approach to improve the accuracy of brain tumour segmentation. Further research and development in this field can help advance the diagnosis and treatment of brain tumours and other medical conditions.