**Edge U-Net: Brain tumor segmentation using MRI based on deep U-Net model with boundary information**

summarize this text : A brain tumor is defined as a mass of tissues that grows gradually from abnormal cells. Whether or not they are malignant, brain tumors can harm nearby brain tissue through the added pressure they create within the rigid skull (Haj-Hosseini et al., 2016). Thus, early detection of brain tumors is essential for prompt and effective therapy (Anitha & Murugavalli, 2016). The human brain may be afflicted by multiple types of tumors, including gliomas, meningiomas, and pituitary tumors (Ricci & Dungan, 2001). Computer-aided diagnostic (CAD) technologies were created and put into use to assist neuro-oncologists in the process of quickly and accurately identifying brain tumors. MRIs represent an invaluable approach that provides detailed images of tissues and organs of the human body.

MRIs remain the most accurate method of localising brain tumors and identifying their dimensions (Wulandari, Sigit, & Bachtiar, 2018). Accurately analysed multi-dimensional data from MRIs can help localise and monitor disease progression and guide treatment. Machine learning has been used for disease detection, prediction, classification, and image segmentation in the context of healthcare images. Segmentation and classification of breast cancer (Debelee, Amirian, Ibenthal, Palm, & Schwenker, 2017; Kebede et al., 2020; Yu, Zhou, Wang, & Zhang, 2022), brain tumors (Gab Allah, Sarhan, & Elshennawy, 2021; Megersa & Alemu, 2015), and such tumors as lung and colon cancers have received the bulk of recent related research (Debelee, Kebede, Schwenker, & Shewarega, 2020). In the current clinical practice, the majority of brain tumor image analysis is performed manually. This is both time-consuming and prone to human error, especially if not performed by a disease expert (Is¸ın, Direkoglu, ˘ & S¸ ah, 2016). Segmentation of healthy and pathologic brain tissue in MRIs, including subregion determination, is critical for analysing brain tumors and selecting treatment plans, as well as for successful cancer research (Bauer, Nolte, & Reyes, 2011). Segmentation of brain tumor MRIs is significantly important for better tumor diagnosis and treatment, as reported in (Menze et al., 2014). The brain tumor segmentation research field has grown significantly in recent years, with a plethora of segmentation methods proposed using various datasets. There are three types of recently developed segmentation models: clustering-based segmentation, supervised machine learning segmentation, and deep learning segmentation. The clustering-based approaches to segmentation work through the partitioning of MRIs into several disjoint groups and identifying a region of interest (ROI) within each image. Pixels with high levels of similarity within each region are classified as such, whereas distinct pixels are classified as such. K-means clustering is an unsupervised machine learning-based algorithm commonly used to extract a ROI from other image elements. It has been investigated as a method of brain tumor segmentation, with acceptable accuracy despite requiring only minimal computational time and power (Almahfud, Setyawan, Sari, & Rachmawanto, 2018). K-means has been found to be most suitable for large datasets. Its drawbacks include insufficient delineation of the tumor region and sensitivity to outliers (Abdel-Maksoud, Elmogy, & Al-Awadi, 2015). To address these vulnerabilities, a more advanced self-adaptive K-means algorithm was created (Kaur & Sharma, 2017). Using the Fuzzy C-Means algorithm, things that are likely to belong to multiple classes are clustered according to their degree of ’belonging’ to each class (FCM). Pixels can thus occupy multiple clusters. When it comes to noise-free image segmentation, FCM outperforms hard-clustering methods like K-means. The efficacy of FCMs decreases in brain tumors, where segmenting MRIs is susceptible to the effects of ’unknown noise’ (Blessy & Sulochana, 2015). A method was proposed by (Sheela & Suganthi, 2019) to overcome the disadvantages of FCMs. For automatic learning, the researchers used the greedy snake algorithm in addition to FCM optimisation. T1 weighted clustering is used to segment tumor tissues captured in brain MRIs using Principal Component Analysis (PCA) algorithms. In (Kaya, Pehlivanlı, Sekizkardes¸, & Ibrikci, 2017), a comparison between the tumor portion and remaining parts of each brain image was performed. The predicted tumor portion could not be clearly identified. Clustering may result in inaccurate detection of tumor size, possibly leading to incorrect treatment, increased morbidity and mortality. Other models of brain tumor MRI segmentation have been based on supervised machine learning, in which the segmentation problem is converted to a tumor pixel classification problem, with the image extracted features serving as input to the model and the desired classes of segmentation serving as output. Supervised machine learning algorithms have been incorporated into a number of proposed segmentation processes of brain tumor images. In the study by (Ma, Luo, & Wang, 2018), automatic segmentation involved a combination of a random forest algorithm and an active contour model. A support vector machine was also used in a study by (Ayachi & Ben Amor, 2009). In that study model, a combination of the two-approaches employed Gabor wavelet transform (IGWT) as feature extractor and K-means for the purposes of clustering. Finally, to achieve the most accurate classification of brain tissue into tumor and non-tumor, a multi-kernel support vector machine (MKSVM) algorithm was then run (Krishnakumar & Manivannan, 2021). In the deep learning methodologies, MRIs typically go through a number of deep learning building blocks, and the features that are extracted determine how MRIs are segmented. In the segmentation of brain tumors, various deep learning models have been used. DCNNs have been enhanced with 3 × 3 filters to achieve automatic brain tumor segmentation (Pereira, Pinto, Alves, & Silva, 2016). To improve segmentation while reducing processing time, an Enhanced Convolutional Neural Network (ECNN) model with an optimised loss function was added. For binary segmentation, a BAT algorithm was developed (Thaha et al., 2019). To solve the problem of imbalanced tumor labels, a multilayer CNN model with a two-pathway architecture was created. For each voxel, the segmentation task was treated as a multiple classification task (Havaei et al., 2017). Another Hybrid CNN model was created with a patch-based method. To address the issue of imbalanced data, the model was programmed to take into account both contextual and local data. This involved using a two-phase training procedure (Sajid, Hussain, & Sarwar, 2019). In contrast to previous models, the Multiscale-CNN (Díaz-Pernas et al., 2021) model was designed with three pathways to capture features at three spatial scales. Fully convolutional networks (FCNs) were developed to generate the label map for the entire image, overcoming the previous methods’ two limitations of computational cost and patch size selection (Long, Shelhamer, & Darrell, 2015). (Ronneberger, Fischer, & Brox, 2015) proposed a U-Net inspired by (Long et al., 2015), which was built using a symmetric fully convolutional network. This model achieved high accuracy, particularly when applied to medical images. A 3D glioma segmentation method based on sequential U-Nets was later introduced (Sun et al., 2019), having a fully automated brain tumor segmentation network based on a stacked U-Net architecture (Ding et al., 2019). Another U-Net-based model is the Attention Res-UNet with Guided Decoder (ARU-GD), in which the learning process is optimised for each decoder block. Each decoder block was also designed to employ its own loss function (Maji, Sigedar, & Singh, 2022). The following section details our proposed MRI brain tumor segmentation framework. Table 1 summarises prior brain tumor segmentation models. Although many deep neural network-based models have achieved success, there are still many challenges and limitations found, including intensity variation of brain tumor tissues due to the imaging protocol being used, modality of images, and random noise inherent in MRI systems (Prima, Ayache, Barrick, & Roberts, 2001), which may result in vague tissue texture and a blurry boundaries of tumor tissue. Furthermore, multiple classes or tissues can coexist within a single pixel of a brain image, a phenomenon known as the partial volume effect in MRIs (Arabahmadi, Farahbakhsh, & Rezazadeh, 2022; Hesamian, Jia, He, & Kennedy, 2019). The rough boundary of a brain tumor is perceived as another type of issue by brain tumor segmentation models. Besides that, brain tumors can vary in location, size, and shape within the brain (Wang & Chung, 2022). We developed a new framework for automated brain tumor segmentation to resolve some of these issues. Brain MRIs are manipulated in this framework to reduce background noise during the imaging process. The U-Net architecture (Ronneberger et al., 2015) inspired the development of a novel encoder-decoder CNN model. To achieve more accurate tumor tissue segmentation, this encoder-decoder model considers brain MRI boundaries and is guided by an edge guidance block (EGB) module. Finally, an efficient loss function aids in dealing with both tumor boundaries and tumor tissue at the same time. The model was tested against the public brain tumor segmentation datasets created by Cheng et al. (Cheng et al., 2015), which contain MRIs of three different types of brain tumors (meningiomas, gliomas, and pituitary tumors). The proposed framework was shown to outperform the state-of-art models of brain tumor segmentation. To address the aforementioned research issues and improve upon the performance of previous segmentation models, this work attempted to introduce the precise segmentation framework through the following contributions: • Developing a U-Net structure-based deep-edge brain tumor MRI segmentation learning model, with a focus on MRI boundaries. Results showed that the framework’s performance was able to outperform current state-of-the-art models. • Suggesting the use of contrast limited adaptive histogram equalisation (CLAHE) in order to enhance MRI contrast and achieve better brain tumor segmentation. • Designing an EGB module that fuses the original MRI boundary features with other MRI features. The outcomes of our framework showed that the EGB had provided more boundary information, improving the ability to detect tumor location and shape recognition. • Developing a novel loss function for our edge deep learning model in which we combined pixel loss and boundary loss, allowing for better recognition of boundaries and, as a result, better pixel values, resulting in a better overall performance. The remaining part of this paper is organised as follows: Section 2 describes how the used dataset was created and provides a detailed description of it. Section 3 provides a description of the proposed framework. Section 4 describes the results of the experiments and discusses the model’s performance. Conclusions and suggestions for possible future work are presented in section 5.

**Result**

The article discusses the importance of early detection of brain tumors and how computer-aided diagnostic (CAD) technologies can assist neuro-oncologists with quick and accurate identification of brain tumors using MRI scans. The article highlights clustering-based segmentation, supervised machine learning segmentation, and deep learning segmentation as recently developed segmentation models for brain tumor MRI segmentation. The article then proposes a new and improved framework for automated brain tumor segmentation that utilizes contrast limited adaptive histogram equalisation (CLAHE) and an edge guidance block (EGB) module to improve recognition of tumor location and shape while reducing background noise during the imaging process. The proposed framework was tested against public brain tumor segmentation datasets and showed superior performance compared to current state-of-the-art models. The article concludes by suggesting possible future applications for the proposed framework.

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Overall, the proposed framework has the potential to improve the accuracy and efficiency of brain tumor segmentation, which is crucial for successful diagnosis and treatment of brain tumors. The article acknowledges the challenges and limitations in brain tumor MRI segmentation, such as the partial volume effect, intensity variation, and variations in size and shape of brain tumors. However, the proposed framework has demonstrated promising results in addressing some of these issues and outperforming current state-of-the-art models.

In conclusion, the article provides valuable insights into the development of new and improved segmentation models for brain tumor MRI analysis using advanced machine learning and deep learning techniques. The proposed framework presents a step forward in improving the accuracy and efficiency of brain tumor segmentation, which can ultimately lead to better patient outcomes and enhance the quality of healthcare for individuals with brain tumors. Further research and advancements in this field can continue to revolutionize the way we diagnose and treat brain tumors.

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The proposed framework's potential for enhancing brain tumor segmentation can also have significant implications for cancer research. Accurate segmentation of brain tumors can aid in analyzing disease progression and developing more effective therapies. Moreover, the proposed framework's utilization of deep learning techniques can potentially be extended to other medical image analysis applications.

Despite the promising results, there are still limitations and challenges that need to be addressed in future research. For example, developing more robust and adaptable models that can address the variability and complexity of brain tumors can help improve accuracy and efficiency. Additionally, integrating multi-modal MRI datasets can provide more comprehensive information for accurate diagnosis and treatment planning. More research is also needed to address the issue of imbalanced data in brain tumor segmentation and improve the generalization of deep learning models across different datasets.

In conclusion, the proposed framework, along with other recent developments in machine learning and deep learning techniques, has shown significant potential in improving the accuracy and efficiency of brain tumor segmentation. Continued research and advancements in this field can lead to significant improvements in the diagnosis and treatment of brain tumors and other medical applications.

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Furthermore, the proposed framework's utilization of contrast limited adaptive histogram equalization (CLAHE) can improve the contrast and quality of MRI images, which can benefit other medical applications in addition to brain tumor segmentation. CLAHE can be used to enhance the contrast of other medical images, such as CT scans, X-rays, and ultrasound images, for better interpretation by medical professionals.

Moreover, as advancements in technology continue to progress, the use of artificial intelligence (AI) and machine learning in medical image analysis is expected to become more widespread. As a result, it is essential to ensure that these technologies are implemented in a safe and ethical manner. Proper validation and testing must be conducted to ensure the accuracy and robustness of AI and machine learning models. Furthermore, privacy and security concerns regarding patient data must also be addressed to ensure patient privacy and confidentiality.

In conclusion, the proposed framework for brain tumor segmentation presents promising results in improving the accuracy and efficiency of brain tumor diagnosis and treatment. Continued research in this field can further advance our understanding of brain tumors and improve patient outcomes. Additionally, the utilization of advanced machine learning and deep learning techniques can benefit other medical image analysis applications, leading to improved diagnosis and treatment of various medical conditions.

It is crucial to recognize that the proposed framework and other advanced medical image analysis technologies are not meant to replace the expertise of medical professionals but rather to enhance their capabilities. Medical professionals play a critical role in interpreting medical images and making accurate diagnoses and treatment decisions. The role of AI and machine learning in medical image analysis is to provide medical professionals with additional information and support, ultimately leading to better outcomes for patients.

In conclusion, the development and utilization of advanced machine learning and deep learning techniques hold great promise for the medical field, particularly in the accurate and efficient analysis of medical images for the diagnosis and treatment of brain tumors and other medical conditions. While there are still challenges to be addressed, continued research and advancements in this field offer exciting opportunities for improving the quality of healthcare and patient outcomes.