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MEDICAL IMAGE SEGMENTATION USING 3-D U-NET

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ABSTRACT

A crucial part of medical image analysis, medical image segmentation has uses in research, therapy planning, and diagnosis. The precision and efficiency of traditional segmentation approaches are limited, necessitating creative alternatives. With its state-of-the-art outcomes, 3D U-Net deep learning has revolutionised the field. The foundations of 3D U-Net and its extensive uses in medical picture segmentation will be covered in this session. Medical image segmentation is the process of accurately identifying different structures within medical pictures, such as those from CT scans, MRIs, or other modalities. The foundation of medical image analysis is this basic activity, which allows medical practitioners to extract useful information for personalised treatment planning, diagnosis, and research advancement. The success of medical interventions depends heavily on the dependability and effectiveness of this segmentation process, which makes 3D U-Net a vital instrument in this important area of technology and healthcare.

The dataset is processed, explored, and strategically split into training and testing sets. Various machine learning models, are trained and evaluated, with their accuracies visually compared. A userfriendly predictive system is implemented, enabling users to input new data for real-time predictions. The trained models are saved for future use.

Keywords- 3-D U-NET, Image Segmentation, Deep learning, Tensor flow, Tumour Pixels, Flair

I. INTRODUCTION

In the past couple of years, deep convolutional networks have revolutionized visual recognition tasks, surpassing previous benchmarks notably in classifying images. This breakthrough stemmed from training large networks with millions of parameters on extensive datasets like ImageNet. While originally geared towards classification, their application expanded to tasks requiring pixel-level localization, particularly in biomedical image analysis. Ciresan et al. innovatively trained networks to predict pixel labels by processing local patches, achieving remarkable success in tasks like the EM segmentation challenge at ISBI 2012. However, this method suffers from inefficiency due to its patch-by-patch processing approach and a trade-off between localization accuracy and contextual understanding. Recent advancements aim to reconcile these issues by leveraging features from multiple layers, offering improved localization while maintaining contextual awareness.

The introduction of the paper discusses the use of deep convolutional neural networks, particularly the UNet architecture, for medical image analysis, with a focus on brain tumour segmentation. The UNet architecture is highlighted for its effectiveness in extracting multi-contextual information from images through skip connections that concatenate features from both encoder and decoder paths. The importance of multi-scaled features in brain tumour segmentation is emphasized, along with the potential limitations of the UNet approach due to the limited use of features. The paper proposes a modified UNet architecture that incorporates densely connected blocks and residual-inception blocks to enhance feature extraction and improve segmentation performance. The proposed architecture is validated on the BRATS 2020 testing dataset, achieving high Dice scores for whole tumour, tumour core, and enhancing tumour segmentation.

II. LITERATURE REVIEW

The research papers present significant contributions to the field of Medical image segmentation. In 2019, Jose Dolz and his team released HyperDense-Net, a hyper-densely linked CNN for multi-modal picture segmentation. By utilising strong connections between layers, it improves the accuracy of segmentation by efficiently capturing fine information in many modalities. Considerable progress in medical image analysis and other multi-modal imaging tasks is anticipated with this method.

A review titled "Deep Learning With TensorFlow" was published in the Journal of Educational and Behavioural Statistics in 2022. This thorough examination evaluates the developments, uses, and difficulties of deep learning

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with the TensorFlow framework. It gives information about the statistical and educational ramifications of this technology, assisting practitioners and researchers in making the most of it.

Priyanka Malhotra and colleagues presented Deep Neural Networks for Medical Image Segmentation in 2022. Their work focuses on improving medical picture segmentation through the application of deep learning algorithms, enabling more precise diagnosis and treatment planning. This method shows great promise for transforming medical imaging analysis and enhancing the quality of patient treatment.

A study named "Medical Image Segmentation Using Deep Learning" was carried out in 2021 by Risheng Wang et al. This extensive study offers insights into the most recent deep learning methods used for segmenting medical images. It is an important resource for scholars and practitioners in the subject as it addresses approaches, difficulties, and future directions.

A thorough investigation on "Medical Image Segmentation Using Deep Neural Networks" was carried out in 2023 by Loan Dao and Ngoc Quoc Ly. In order to accurately segment medical images, their research examines a variety of deep learning architectures and techniques. By shedding light on the difficulties and developments in this crucial field, their work advances applications in the diagnostic and healthcare fields.Collectively, these papers represent a diverse array of methodologies and insights that collectively advance the field of heart Medical image segmentation

III. METHODOLOGY

A. Network Architecture:

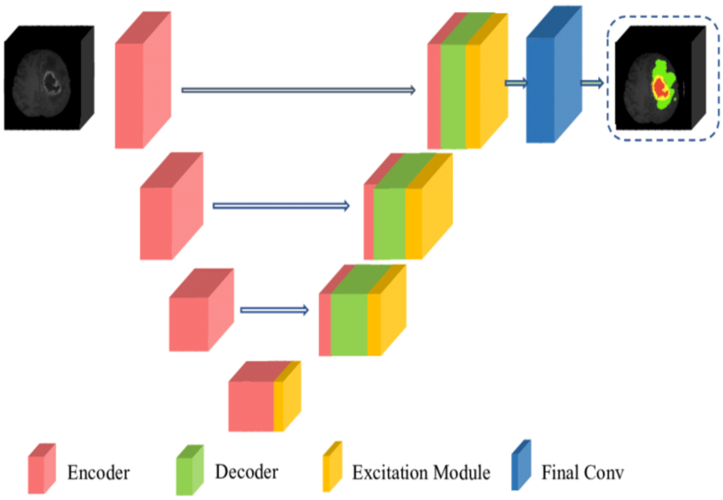

Fig 1- 3D U-Net Architecture

The network architecture comprises two main paths: a contracting path on the left and an expansive path on the right. The contracting path involves repeated 3x3 convolutions, ReLU activations, and Sigmoid Functions for downsampling, doubling feature channels at each step. The expansive path includes upsampling, convolution to halve feature channels, concatenation with corresponding cropped feature maps from the contracting path, and additional convolutions with ReLU. Border cropping is necessary due to convolutional losses. A final 1x1 convolution maps features to desired classes. The network boasts 23 convolutional layers. To ensure seamless segmentation map tiling, input tile size must align with even dimensions for all 2x2 max-pooling operations.

B. Proposed Method:

The proposed method in the paper introduces a modified UNet architecture for brain tumour segmentation. This architecture emphasises the idea of feature reusability by incorporating densely connected blocks in both the encoder and decoder paths to extract multi-contextual information from images.Additionally, residual-inception blocks (RIB) are utilized to merge features of different kernel sizes, enabling the extraction of local and global information. The study validates the proposed architecture on the BRATS 2020 testing dataset, achieving high Dice scores for whole tumour, tumour core, and enhancing tumour segmentation. The key contributions of the proposed method include the novel use of densely connected blocks, the integration of RIB for feature merging, and the achievement of state-of-the-art performance compared to other recent methods.

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IV. RESULT AND DISCUSSION

A. Dataset: The experimental results section of the paper discusses the dataset used for training and evaluation, which includes the BRATS 2018, BRATS 2019, and BRATS 2020 datasets. These datasets are provided by the organizers of the BRATS challenges and consist of various independent datasets for training, validation, andtesting. The datasets include different modalities such as native (T1), post-contrast T1-weighted (T1ce), T2-weighted (T2), and Fluid Attenuated Inversion Recovery (FLAIR) images for each patient. The training datasets are further classified into high-grade glioblastoma (HGG) and low-grade glioblastoma (LGG). The paper mentions having access to the training and validation datasets of BRATS 2018 and BRATS 2019. The utilization of these datasets allows for the training and evaluation of the proposed brain tumour segmentation model.

B. Implementation Details: The experimental results and implementation details section of the paper provide insights into the methodology and outcomes of the brain tumour segmentation study. The implementation details highlight the normalization of data from multiple scanners and imaging protocols to avoid biases in the neural network. Patches of size 128x128x128 are extracted from four MRI modalities for input. The training process involves a five-fold cross-validation approach with 300 epochs per training cycle, using the Adam optimizer with specific learning rate adjustments. Augmentation techniques like random rotations and mirror flips are applied during training to enhance model generalization.

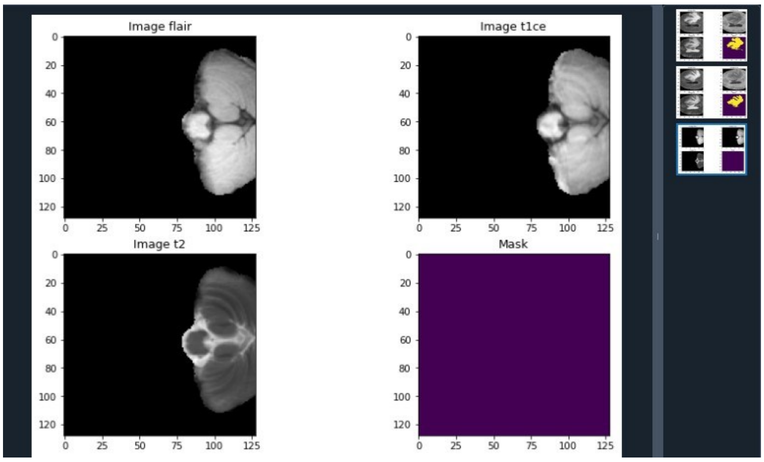

Fig 2- Mask image showing no tumour

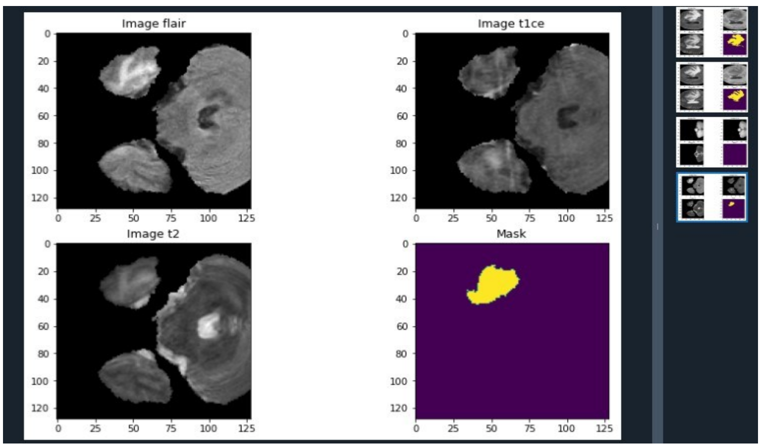

Fig 3- Mask image showing tumour

In the experimental results, the proposed model is evaluated on the BRATS 2018, 2019, and 2020 datasets, showcasing the effectiveness of the modified UNet architecture. The study reports high Dice scores for whole tumour, tumour core, and enhancing tumour segmentation on the BRATS 2020 testing dataset. The model's performance is compared to other methods, demonstrating state-of-the-art results in brain tumour segmentation. The section emphasizes the importance of hyperparameter tuning and the adoption of a multi-class dice loss function to optimize model performance.

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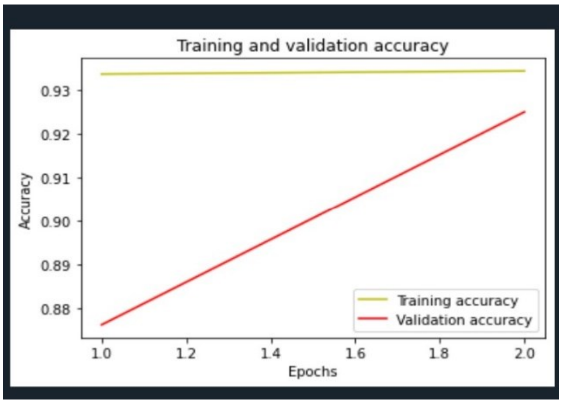

Fig 4- Training and Validation Accuracy

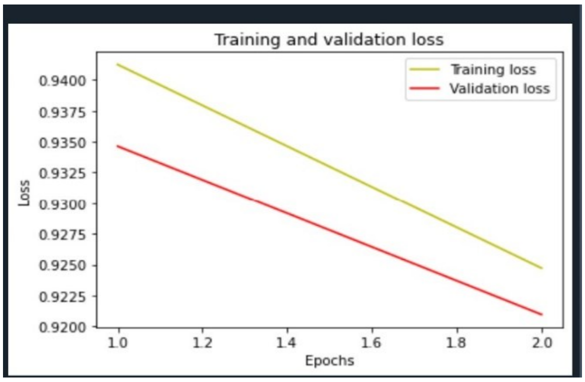

Fig 5- Training and validation loss

V. CONCLUSION

The discussion and conclusion section of the paper summarizes the key findings and implications of the proposed 3D UNet model for brain tumour segmentation. The study highlights the unique architecture of the model, which includes dense connections at each level of the encoder-decoder paths and residual-inception blocks for extracting local and global contextual information. The model's performance is evaluated on the BRATS datasets of 2018, 2019, and 2020, showcasing its ability to achieve state-of-the-art results in brain tumour segmentation.

The discussion section emphasizes the significance of the proposed model's features, such as multi-contextual information extraction and feature reusability through densely connected blocks. The study also mentions ongoing research efforts to further improve the segmentation of enhancing tumour regions by exploring post-processing strategies and augmentation techniques based on different classes.

In conclusion, the paper underscores the effectiveness of the proposed 3D UNet model in accurately segmenting brain tumours, particularly in the context of the BRATS datasets. The study's contributions include the novel architectural modifications that enhance feature extraction and the model's ability to achieve high segmentation accuracy. The conclusion also hints at future research directions aimed at refining the segmentation of specific tumour regions and optimizing model performance further.

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