IMPROVING 3D LESION SEGMENTATION ROBUSTNESS AGAINST IMAGE COMPRESSION IN MULTIPLE SCLEROSIS

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1. INTRODUCTION

Accurate segmentation of white matter lesions (WMLs) in MRI is crucial for the diagnosis and prognosis of multiple sclerosis (MS) [1, 2]. Given that this manual process is laborious and time consuming, several deep learning (DL)-based methods have been proposed to automate the process [3]. Data transfer and storage are key for DL methods due to their requirement for large amounts of data, making image compression (IC) a powerful tool to enhance data management efficiency. Nonetheless, lossy IC can impact image quality, potentially affecting the accuracy of DL tasks. While related works have studied the effect of IC on DL-based tasks in medical imaging [4, 5, 6], no work has studied the impact of IC on DL-based segmentation of WMLs yet. In this work, we propose an iterative fine-tuning approach to improve the robustness of 3D U-Net segmentation against IC of WMLs in MS. We show that our proposed approach can handle compression ratios (CRs) up to 64:1 while only slightly decreasing segmentation performance.

2. MATERIALS AND METHOD

Dataset. 3D MRI FLAIR images from 63 MS patients aged 22-66 were acquired at Saint-Luc University Hospital (Brussels, Belgium) using a 3T Signa Premier GE scanner. WML annotations were performed by two experts upon consensus*. The dataset was split into a training set of 34 patient scans, a validation set of 11 patient scans and an independent test set made up of 18 patient scans.

Data compression. To achieve visually lossless IC, we use the open-source JPEG 2000 (J2K) algorithm. The choice of J2K is supported by its high-CR efficiency and its widespread deployment into various medical imaging tools such as the DICOM standard [7]. The 3D MRI scans were compressed as individual 2D slices before reassembly.

Base model. The base model uses a 3D patch-based U-Net architecture for semantic segmentation of WMLs [8, 9]. It is trained for 300 epochs on the uncompressed training set. To test the robustness of the base model against J2K compression artifacts, seven tests were performed on the test set which was compressed at CRs of $\{2, 8, 24, 32, 48, 56, 64\}$:1 respectively.

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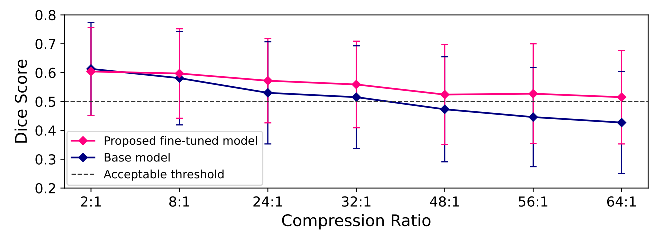

Fig. 1: Semantic segmentation performances of the proposed fine-tuned model versus the base model tested on compressed images at increasing compression ratios.

Proposed fine-tuned model. The proposed model extends the base model by taking its weights and performing seven fine-tuning iterations, for 15 epochs each, on the same training set compressed at CRs of $\{2, 8, 24, 32, 48, 56, 64\}$:1 respectively. The model is tested after each iteration on test set which was compressed at each CR. The iterative fine-tuning helps the model learn and filter out IC artifacts at higher CRs.

Acceptable threshold. In alignment with related works and to allow for a fair comparison, we set an empirical threshold for an acceptable Dice score at 0.5, corresponding to a peak performance drop of 13% [4].

3. RESULTS

As shown in Fig. 1, we observe that, for equivalent segmentation performances, the proposed fine-tuned model can handle CRs up to 64:1 compared to maximum CR of 32:1 for the base model. In comparison with related works which have studied the resilience of DL-based tasks in medical imaging to IC [4, 5, 6], our proposed fine-tuned model achieves up to a twofold increase in robustness to IC artifacts.

4. CONCLUSION

This study demonstrates that iterative fine-tuning enables 3D U-Net to accurately segment MS WMLs in MRI even under high CRs. The results build upon previous works endorsing the use of IC in medical data management and showing that it can be effectively deployed with marginal performance drop.

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5. REFERENCES

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