Foundation Model–Enhanced Classification of Paramagnetic Rim Lesions in Multiple Sclerosis

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Background: Recent research has applied task-specific Deep Learning (DL) networks to classify Paramagnetic Rim Lesions (PRLs) in people with Multiple Sclerosis (pwMS). Yet, DL typically requires large, well-annotated datasets, which are time-consuming to generate and often not widely available. In contrast, foundation models—pretrained on large, heterogeneous datasets without a single task-specific objective—have recently shown strong performance across multiple clinical applications, potentially owing to their capacity to learn generalizable, context-sensitive representations.

Objectives: To improve automated PRL classification in pwMS by fine-tuning an existing foundation model.

Methods: In this prospective monocentric study (2018–2022), 3D brain MRI scans from 180 pwMS (mean age 47 ± 14 years; 108 females) were acquired at 3T, 1mm isotropic resolution, including fluid-attenuated inversion recovery (FLAIR), magnetization-prepared 2 rapid acquisition gradient echoes (MP2RAGE), and T2*-weighted segmented 3D echo-planar imaging, from which quantitative susceptibility mapping (QSM) images were reconstructed. Lesion masks were generated automatically and corrected manually on FLAIR, including the splitting of confluent lesions. Ground truth labels were also defined by two expert raters, identifying 453 PRLs on QSM. A U-Net–based foundation model (Gordaliza et al., 2026), pretrained on MRI data from over 11,000 subjects, was fine-tuned (training: 96 pwMS, 5'049 lesions; validation: 47 pwMS, 1'509 lesions) and tested on a

separate hold-out set (37 pwMS, 1’709 lesions). Its inputs are patches of 64x64x64 voxels extracted from QSM and MP2RAGE centered on lesion candidates.

Results: The fine-tuned model achieved a best mean validation F1 score of 0.809 ± 0.035. On the hold-out test set, it reached an F1 score of 0.775, with precision of 0.754 and recall of 0.801. Without using pretrained weights, the same architecture achieved a validation F1 score of 0.741 ± 0.031 and a hold-out test score of 0.751. On the same data, a task-specific DL network (Spagnolo et al., 2026) achieved a validation F1 score of 0.737 ± 0.027 and a test score of 0.711.

Conclusion: Foundation models can enhance PRL classification, potentially supporting more accurate detection and enabling more personalized treatment strategies in pwMS.

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