Radiomic feature robustness affected by magnetic resonance field strength for patients with Alzheimer's Disease

Jiqing Huang[1], Yi Chen[2,3], Christophe Phillips[1]

[1]GIGA-Institute, CRC-Human Imaging, University of Liège

[2]AMIIC-Lab, College of Computer Science and Technology, Guizhou University

[3]The D-Lab, Department of Precision Medicine, Maastricht University

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1 Introduction

Alzheimer's disease (AD), an irreversible neurodegenerative disorder affecting over 55 million people worldwide[1], presents a critical public health challenge intensified by aging populations. Advances in neuroscience and radiomics now enable the systematic tracking of AD progression through conventional MR images[2]. Recent studies have increasingly focused on evaluating the impact of MRI field strengths on diagnostic performance, particularly modeled as classification tasks[2-4]. The radiomics features extracted from MR images, correlating with hippocampal atrophy and cortical thinning, may be considered valuable biomarkers reflecting pathological and functional changes. However, a critical gap persists in understanding how individual MRI-derived features behave across field strengths. In brain imaging, MR images are acquired using different manufacturers, magnetic field strengths, and acquisition param-

eters. These variations can significantly affect further radiomics studies, especially different magnetic field strength. In this study, our objective was to assess the robustness of specific radiomic features across different MRI field strengths and evaluate their diagnostic value for AD detection.

2 Methods

This retrospective study analyzed 253 subjects from the ADNI database (https://adni.loni.usc.edu) with paired 1.5T and 3T MRI scans . Of these, 191 subjects were included because their scans were conducted within a 3 month period: 41 Alzheimer's disease (AD) patients, 88 mild cognitive impairment (MCI) patients, and 62 cognitively normal controls (NC) (age 74.67 ± 7.21 years; 95 males/96 females). All scans utilized standardized T1-weighted sequences with harmonized parameters across scanners/sites under quality control at the Mayo ADIR lab. Bilateral hippocampi were segmented based on HippoDeep method[5] for 1.5T and 3T scan respectively. Subsequently, radiomics features were extracted from the segmented hippocampi using Pyradiomics[6]. To evaluate the reproducibility and robustness of the extracted features across 1.5T and 3T scans, the nonlinear concordance correlation coefficient (NCCC) and the Wilcoxon signed-rank test (WSR) were used. The acceptable stable features (NCCC $>$ 0.6) were used for classification tasks to distinguish between NC and MCI, as well as between MCI and AD. Rather than using the features that passed the Wilcoxon signed-rank test, the ten most informative features were selected based on mutual information scores. A Random Forest classifier was trained on the training set (80%), and its performance was evaluated on the testing set (20%). To enhance robustness and reduce the risk of overfitting, five-fold cross-validation was performed within the training set during model development.

3 Result

Figure 1 shows representative hippocampal segmentation from NC, MCI, and AD subjects' MRI at both 1.5T and 3T field strengths. Among the 120 radiomic features, 27 features displayed acceptable concordance between 1.5T and 3T (NCCC $>$ 0.6). Most of the features were

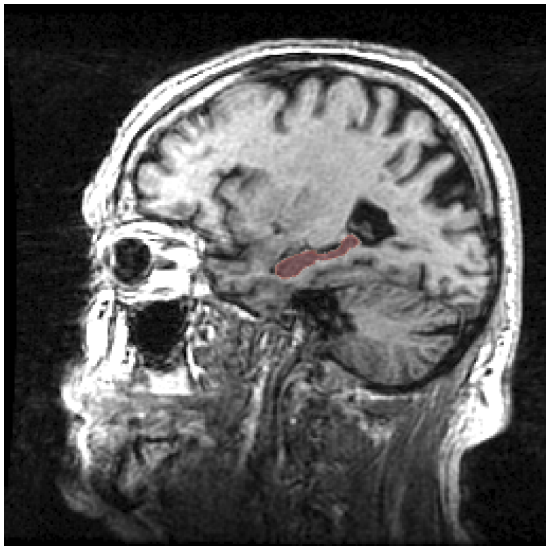
shape-related, as shown in Figure 2. Figure 3 shows the classification performance based on area under curve (AUC) for distinguishing NC-vs-MCI and MCI-vs-AD groups at both 1.5T and 3T field strengths.

4 Discussion

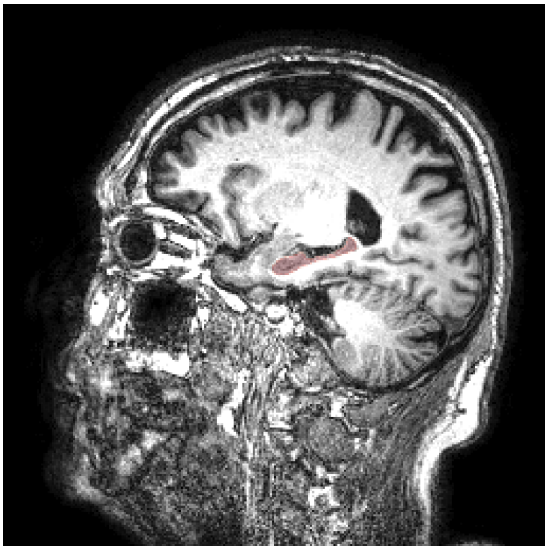
In this work, several stable features were identified that were not significantly affected by field strength and were able to preserve hippocampal characteristics across different field strengths. Using stable features, four Random Forest classifiers were constructed to successfully classify subjects into NC, MCI, or AD. These models achieved above 80% area under curve (AUC) for MCI-vs-NC, i.e. strong discrimination. However, differentiating MCI from AD remains challenging, with 71% and 76% AUC, respectively for the 1.5T and 3T MRIs. Potential reasons for this are that i) MCI encompasses diverse range of microstructure changes, making it a complex condition to classify, and ii) subtle features captured by NCCC are insufficient to detect changes in MCI progression. Therefore, future research may need to incorporate more refined MCI stratification strategies and employ enhanced feature techniques for comparing feature robustness to improve the classification performance between MCI and AD.

5 Conclusions

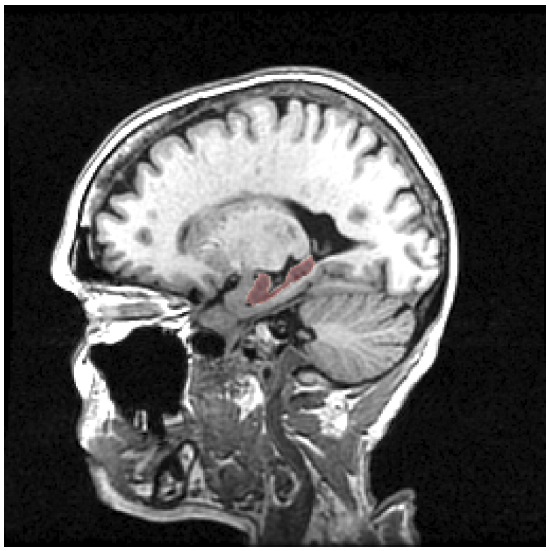
The common radiomics features across 1.5T and 3T demonstrate potential for distinguishing NC, MCI and AD. Additionally, those stable features truly possess generalizable diagnostic value for early Alzheimer's disease.



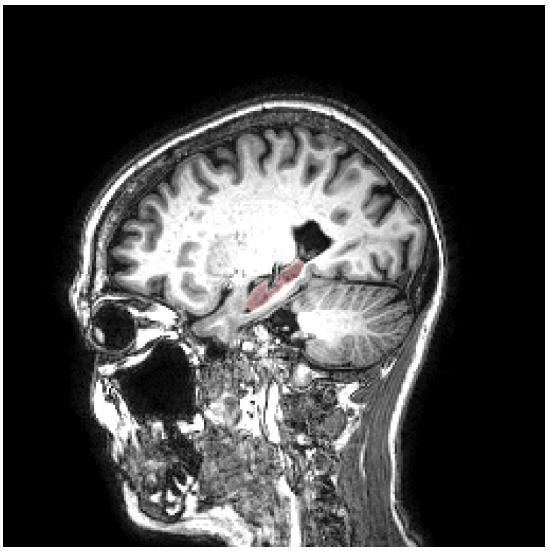
(a) (a) NC 1.5T



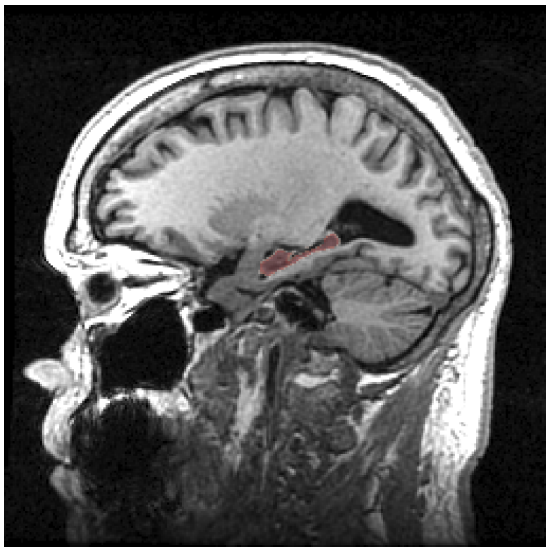
(b) NC 3T



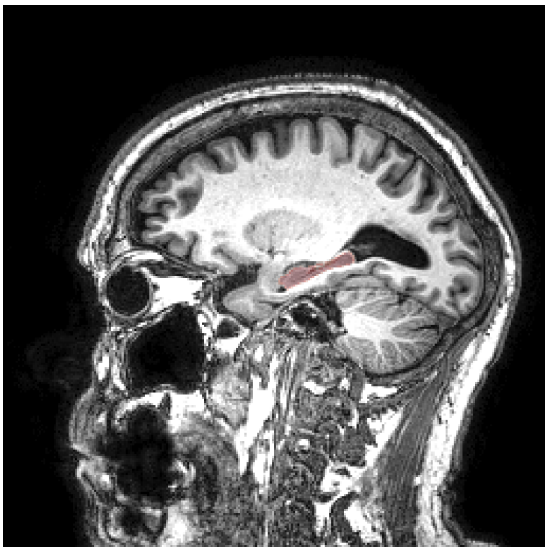
(c) MCI 1.5T



(d) MCI 3T



(e) AD 1.5T



(f) AD 3T

Figure 1: Visualization of bilateral hippocampi in NC, MCI, and AD subjects under 1.5T and 3T MRI scanners. **NC**: Normal Cognition**MCI**: Mild Cognitive Impairment **AD**: Alzheimer's Disease

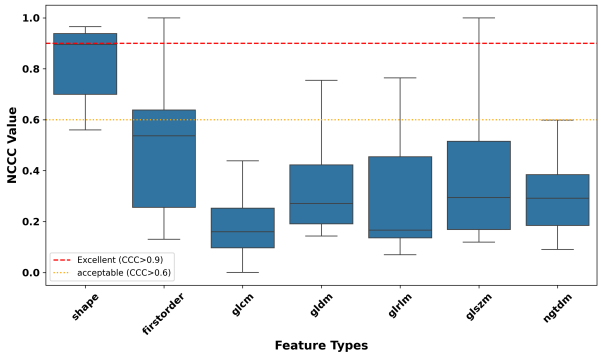
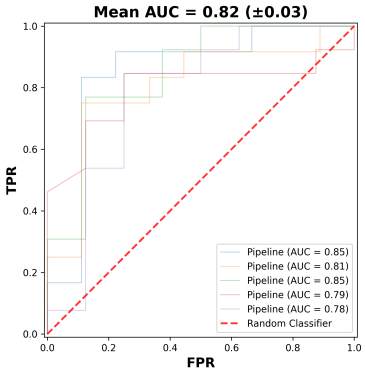
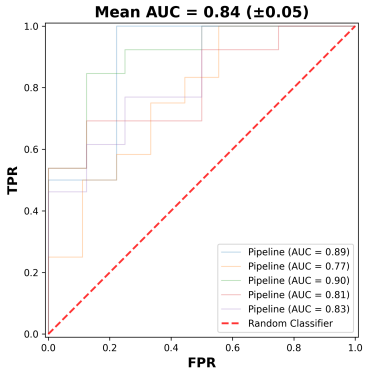


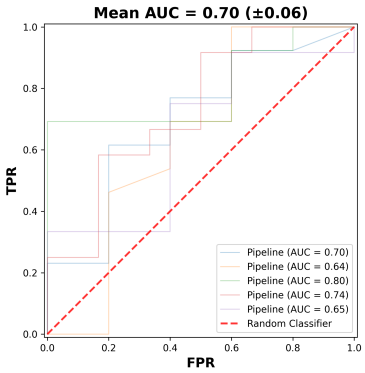
Figure 2: Stability of radiomics features under 1.5T and 3T MRI **glcm**: Gray Level Co-occurrence Matrix **gldm**: Gray Level Dependence Matrix **glrlm**: Gray Level Run Length Matrix,**glszm**: Gray Level Size Zone Matrix,**ngtdm**: Neighboring Gray Tone Difference Matrix



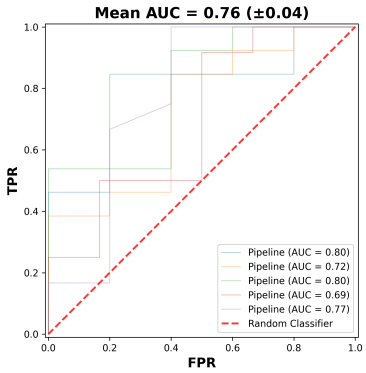
(a) NC vs MCI (1.5T)



(b) NC vs MCI (3T)



(c) MCI vs AD (1.5T)



(d) MCI vs AD (3T)

Figure 3: Random Forest performance on stable features for NC-vs–MCI and MCI-vs–AD classification from 1.5T and 3T MRI. **MCI**: Mild Cognitive Impairment, **AD**: Alzheimer's Disease, **TPR**: True Positive Rate**FPR**: False Positive Rate

6 References

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