Impact of Magnetic Field Strength on Radiomics-Based Knee Injury Diagnosis

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Synopsis

Motivation: MRNet is a widely used database for knee injury diagnosis. While several classifiers achieve high accuracy on internal datasets, their performance often declines on external data. Researchers primarily attributed this degradation to site effects, though the role of magnetic field strength (MFS) variations has likely been underestimated.

Goals: To disentangle the effects of MFS in knee injury classification.

Approach: MFS was inferred using a Gaussian mixture model. Radiomic features were evaluated through one-way ANOVA to quantify MFS effects.

Results: Preliminary results suggest that MFS substantially influences radiomic feature distributions and introduces bias, particularly in imbalanced datasets.

Keywords: RADIOMICS, MAGNETIC FIELD STRENGTH, GAUSSIAN MIXTURE MODEL, SITE EFFECTS, KNEE INJURY

Impact

Magnetic field strength (MFS) substantially affects feature distributions and may introduce bias into machine learning-based disease classification. These findings highlight the need to balance field strength variations in multi-site MRI datasets to enhance model generalization and clinical applicability.

Introduction

MRI remains the imaging modality of choice for assessing knee injuries. Recent studies have reported that radiomics- and deep learning–based methods can achieve high diagnostic accuracy in classifying specific knee pathologies, particularly anterior cruciate ligament (ACL) and meniscal tears. The MRNet [1] challenge dataset, including over 1,000 subjects, has been extensively used and continues to yield improving internal accuracy in the classification tasks. However, when these well-tuned models are applied to external validation cohorts, performance often drops markedly, limiting clinical utility[1-3]. This degradation is commonly attributed to site-related factors (e.g., scanner manufacturer, acquisition protocol)[4]. However, these explanations may be incomplete: heterogeneity in MFS may also play a significant role[5]. In this study, we analysed how MFS effects drive systematic variation in radiomic feature representations.

Methods

Among the publicly available datasets, the MRNet cohorts have become benchmarks for knee injury diagnosis, as listed in Table 1. We analysed the effect of MFS on MRNet tasks. Since MRNet does not provide MFS metadata, we inferred MFS using a Gaussian Mixture Model (GMM) with a slice-count prior, retaining subjects with >95% clustering confidence. The impact of the inferred 1.5 T and 3 T groups was then evaluated across the abnormality, meniscal tear, and ACL tear tasks. Cartilage was segmented using nnU-Net[6], after which a peri-cartilaginous rectangular voxel region of interest (ROI) was defined for feature extraction. Radiomic features were then extracted within the ROI using PyRadiomics. For injury specific analyses, we used axial PD-weighted images for abnormalities and meniscal tears (as recommended by the original study[1]) and sagittal T1-weighted images for ACL tears to assess MFS effects. To mitigate redundancy, principal component analysis (PCA) was applied to the extracted radiomic features to retain 20 principal components; mutual information with the disease label was then used to select the 10 most informative components. Finally, ANOVA was performed to assess the influence of MFS on feature separability.

Results

Using the slice count information listed in Table 1, the GMM successfully split MRNet participants into 1.5 T and 3 T cohorts, as shown in Figure 1a. Figure 1b shows class prevalence stratified by MFS. Following nnU-Net-based segmentation, a rectangular-voxel ROI (three slices per participant) was defined. Representative examples are shown in Figure 2. ANOVA results are summarized in Table 2. For MFS, feature-level effects are reported across all three lesion categories (abnormality, meniscal tear, and ACL).

Discussion

The GMM separated MRNet data into 1.5 T and 3 T cohorts. Disease prevalence differed into abnormality (65.52% vs. 89.55%), ACL (24.60% vs. 18.87%), and meniscus (24.83% vs. 44.85%). These findings indicate clear distribution shifts between the 1.5 T and 3 T subsets. Across the three diagnostic tasks, the influence of MFS increased progressively from ACL to abnormality to meniscus detection. For ACL analysis, no significant difference was observed between radiomic features and MFS effects, indicating that when the MFS factor is balanced, radiomic features exhibit minimal domain-related bias. For abnormality detection, two of ten disease-related features showed significant differences across MFS groups, suggesting mild but detectable field-strength sensitivity. In contrast, the meniscus analysis revealed a clear MFS effect, with five of ten features showing significant differences among MFS. Among these, the most responsive feature reached an F-value of 34.95 ($p < 0.001$), indicating substantial differences between the 1.5 T and 3 T cohorts. These results highlight the importance of explicitly distinguishing MFS and other site effects (e.g., scanner manufacturer, acquisition protocol), as MFS imbalance can systematically bias radiomic feature representations and should be modeled or corrected during preprocessing and model development. This study has certain limitations. Future work will use more precise ROI to better characterize the influence of different factors. We also plan to explore alternative data splits and conduct a more continuous assessment of MFS and others site effects to gain a deeper understanding of their impact on radiomic feature variability.

Conclusion

This study demonstrates that radiomics features remain largely domain-agnostic under balanced condition. Moreover, data imbalance can introduce systematic biases related to MFS effect, challenging the robustness and reproducibility for clinical translation and implementation.

Code/Data Availability statement

The MRNet dataset is publicly available on Kaggle and its official homepage. The code used in this study will be made publicly accessible at https://github.com/cyclotronresearchcentre

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Figures

Dataset	MRNet
Scanner Field Strength	GE 1.5 T and 3.0 T systems (3 T: 56.6%)
Population	1,370 knee MRI cases: • ~81% (1,104) abnormal exams • ~23% (319) ACL tears • ~37% (508) meniscal tears *[120 tuning cases inaccessible]*
Sequence	Sagittal: PD-FS weighted Coronal, Axial: PD weighted
Number of Slices	1.5 T: Sagittal 24 / Coronal 20 / Axial 30 3 T: Sagittal 42 / Coronal 44 / Axial 44

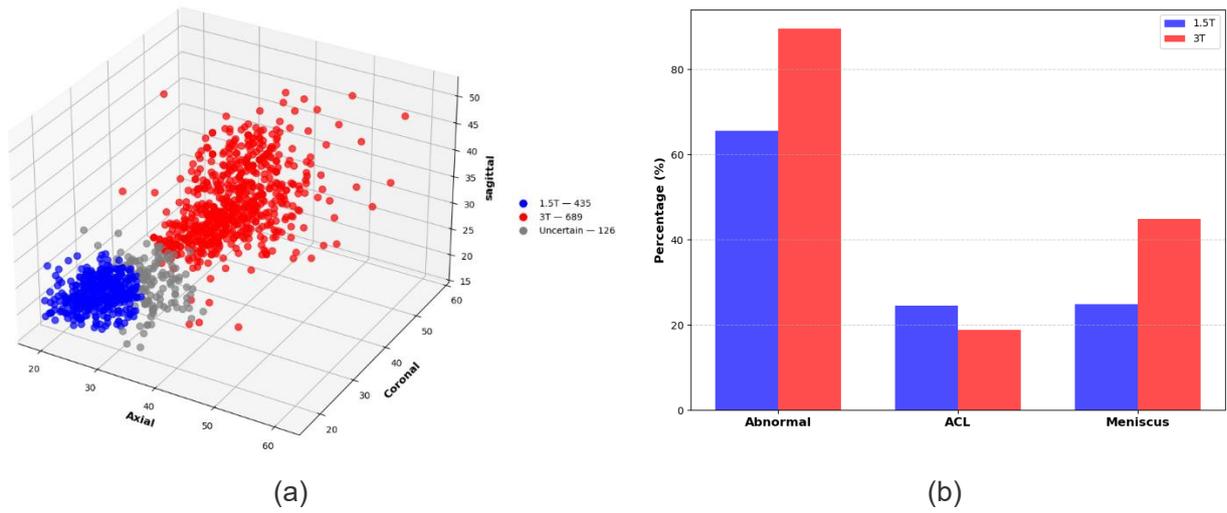**Table 1.** Summary of the MRNet Dataset and Typical Slice Numbers

Figure 1. Cohort separation and magnetic field strength distribution in MRNet. (a) GMM-based classification of 1.5 T and 3 T cohorts (posterior probability > 0.95). (b) Sample distribution by inferred field strength.
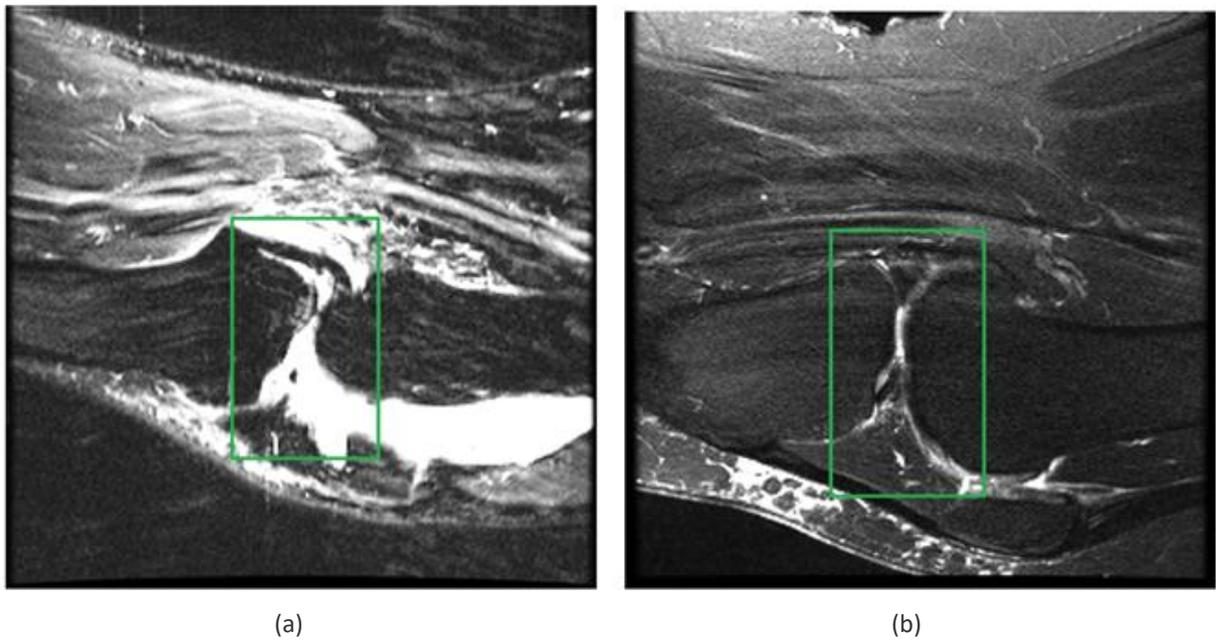

(a)   (b)

Figure 2. Representative ACL MRI images: (a) MRNet 1.5 T, and (b) MRNet 3 T.

Disease	Number of significant features	F-value range	p-value range
ACL tear	0/10	0.6 – 2.0	0.22 – 0.65
abnormality	2/10	0.5-3.2	0.04 – 0.68
Meniscal tear	5/10	5.8 – 34.95	<0.001-0.4

Table 2. Statistical analysis (ANOVA) of MFS effects on radiomic features