IMPERIAL

Automatic Segmentation of the Knee using Artificial intelligence on a Novel MRI Scanner: MADI (Magic Angle Directional Imaging)

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Introduction:

Background:

- ACL & Meniscal Injuries are common and cause major problems in young & athlete patients
- MADI uses the magic angle effect to directly visualise collagenous structures on MRI
- Tractography allows us to take a region of interest (ROI) and visualise fibre orientation, direction, and integrity in detail
- Manual segmentation of the ROI is a time-consuming process, giving rise to automatic methods e.g. Convolutional Neural Networks.

Aims:

- Prepare a novel MADI MRI dataset
- Benchmark two deep learning segmentation models (3DU-Net & nnU-net) on MADI and conventional datasets
- Evaluate segmentation outputs quantitatively and qualitatively using 3D renders

Methods:

Datasets:

Name	Volumes	Patients	Segmented Structures	Segmentation Source	Resolution (mm)
IWOAI	176	88	Cartilage (Patella, Tibia), Meniscus	Expert Radiologist	0.36x0.36x0.7
OAI-ZIB	507	507	Cartilage (Femur, Tibia), Bone (Femur, Tibia)	Expert Radiologist	0.36x0.36x0.7
MADI	183	23	Meniscus, ACL	Radiologist, Radiographer, PhD Student	1.0x1.0x1.0

Deep Learning Models:

3DU-Net: CNN designed for volumetric medical image segmentation. Not robust + requires manual tuning
nnU-Net: CNN based on U-Net with a self-configuring pipeline and automatic tuning. Strong generalisation

Evaluation metrics:

Dice Score (DSC): measures overlap between predicted and ground truth segmentation – % of shared pixels
Intersection Over Union (IOU): measures overlap but penalises mismatches & over-segmentation more heavily

Results:

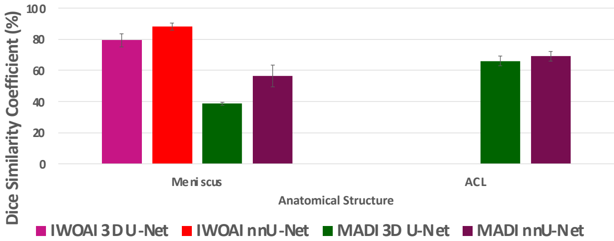
IWOAI:

Structure	Model	Dice (%) ± SD
Meniscus	3D U-Net	79.29 ± 4.21
Meniscus	nnU-Net	*88.09 ± 2.29*
Tibial Cartilage	3D U-Net	82.81 ± 4.69
Tibial Cartilage	nnU-Net	*88.21 ± 3.04*
Patellar Cartilage	3D U-Net	63.07 ± 16.45
Patellar Cartilage	nnU-Net	*84.98 ± 7.81*

MADI:

Structure	Model	Dice (%) ± SD
ACL	3D U-Net	66.09 ± 0.03
ACL	nnU-Net	*69.04 ± 2.63*
	p-value	< 0.01
Meniscus	3D U-Net	38.56 ± 6.39
Meniscus	nnU-Net	*56.41 ± 17.32*
	p-value	< 0.01

Dice Score Comparison by Structure and Model



nnU-Net on IWOAI


Figure 11a – Raw MRI


Figure 11b – Raw MRI + Ground Truth label


Figure 11c – Raw MRI + predicted segmentation

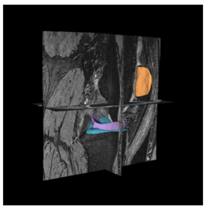


Figure 11d – 3D render of predicted segmentation with slice intersections

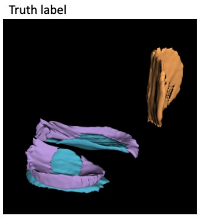


Figure 11e – 3D render of ground truth label

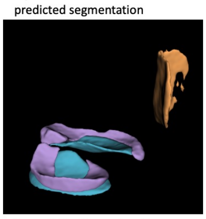


Figure 11f – 3D render of predicted segmentation

Meniscus (purple)
Tibial Cartilage (blue)
Patellar Cartilage (orange)

nnU-Net on MADI

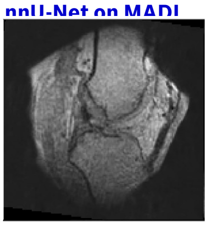


Figure 15a – Raw MRI

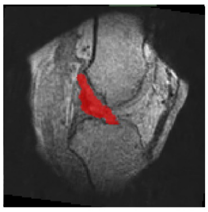


Figure 15b – Raw MRI + Ground Truth label

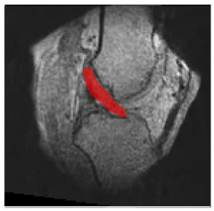


Figure 15c – Raw MRI + predicted segmentation

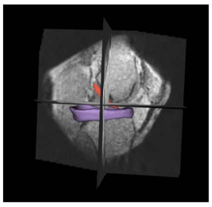


Figure 15d – 3D render of predicted segmentation with slice intersections

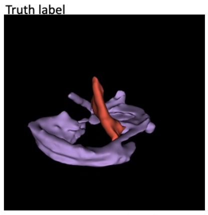


Figure 15e – 3D render of ground truth label

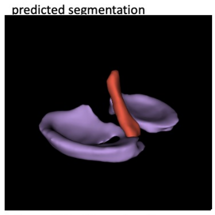


Figure 15f – 3D render of predicted segmentation

Meniscus (purple)
ACL (red)

Limitations:

- Lack of Public ACL datasets limits benchmarking
- Small & homogenous MADI dataset
- MADI label variability and high signal to noise ratio
- Misleading evaluation Metrics for small structures

Clinical Translation:

- MADI offers non-invasive, collagen-sensitive MRI
- AI Segmentations improve tractography accuracy
- MADI has the potential to reduce diagnostic arthroscopy and provide a virtual arthroscopy

Future Work:

- Expand and diversify the MADI dataset
- Improve label quality and standardisation
- Explore transformer-based models, image resampling and noise reduction

Conclusion:

This research presents the first deep learning-based segmentation of ACL and meniscus on MADI data. Despite reduced quantitative performance, qualitative results demonstrate strong anatomical plausibility and usefulness for downstream tractography, laying the groundwork for virtual arthroscopy.

References:

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