Development of an algorithm for automatic detection of meniscus tears in knee magnetic resonance imaging (MRI) scans.

Chong Sook Yee

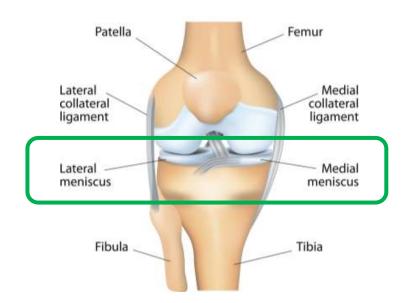
Research Aim

 Determine if a model could succeed in the clinically important task of detecting meniscus tears in knee magnetic resonance imaging (MRI) scans.

- Improve access to quality MRI diagnoses in the absence of specialised radiologists, or to reduce the workload of specialized radiologists.
 - While use of MRI and CT scans have increased, number of radiologists have remained almost the same (McDonald et al., 2015, Kumamaru et al., 2018).

Introduction

- Meniscus is important for:
 - Knee stability
 - Load transfer/distribution (shock absorber)
 - Preserves articular cartilage



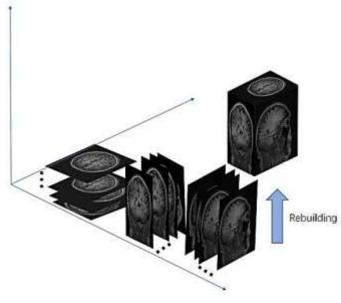
Introduction

• A meniscal tear is a frequent orthopaedic diagnosis and an early indication of osteoarthritis (OA).

Knee MRIs are not typically ordered for asymptomatic patients.

• 61% of randomly selected participants showed meniscal tears in their knees during magnetic resonance imaging (MRI) scans. They have not had any pain, aches, or stiffness during the previous months (Englund et al., 2008).

MR imaging



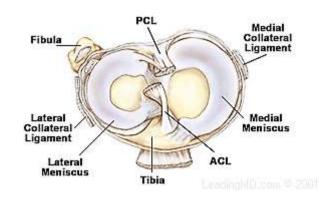
3D planes scanned

Image	Signal intensity	Clinical use
T1-weighted	 Fat bright Muscle intermediate Water, tendon, cartilage dark 	 Good anatomical detail Low sensitivity for soft tissue Good for meniscal pathology
T2-weighted	Water brightFat intermediateMuscle and cartilage dark	Good for soft tissue injuries, especially tendon
Proton density (PD) weighted	Fat brightWaterintermediateTendon andcartilage dark	Good for viewing meniscus and ligaments

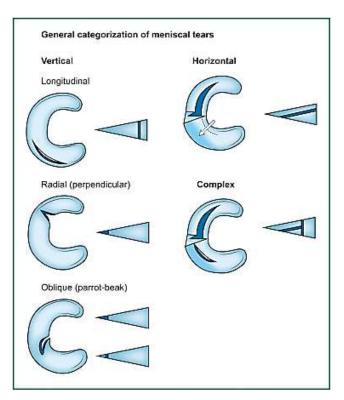
MRI pulse sequences

Dataset

Plane	Plane	MRI	Training set	Validation set	Pulse sequence
Sagittal			1130	120	T2-weighted
Frontal/ Coronal			1130	120	T1-weighted
Axial/ Transverse/ Horizontal			1130	120	PD-weighted

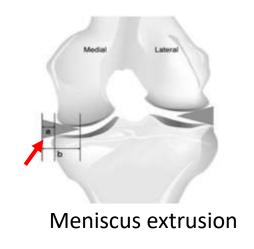


Healthy meniscus



Meniscal tears (Lecouvet et al., 2018)

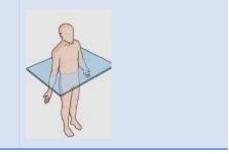
Plane Frontal/ Coronal

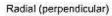


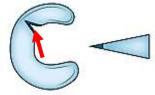


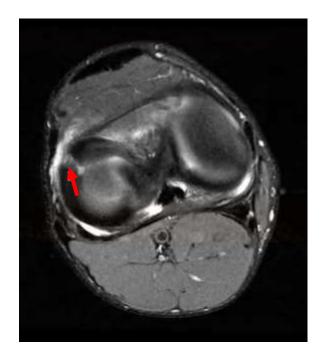
Plane

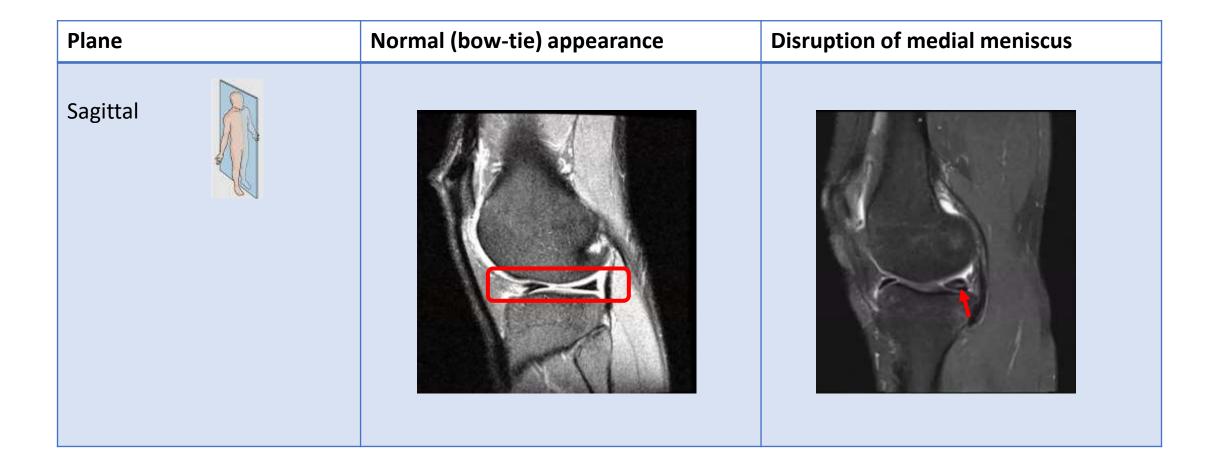
Axial/ Transverse/ Horizontal









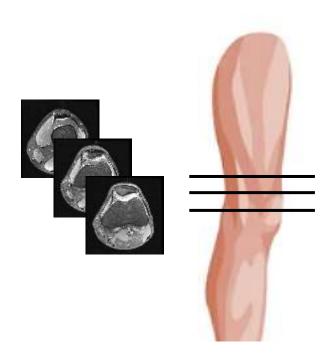


Dataset

Plane	Plane	MRI	Training set	Validation set	Pulse sequence
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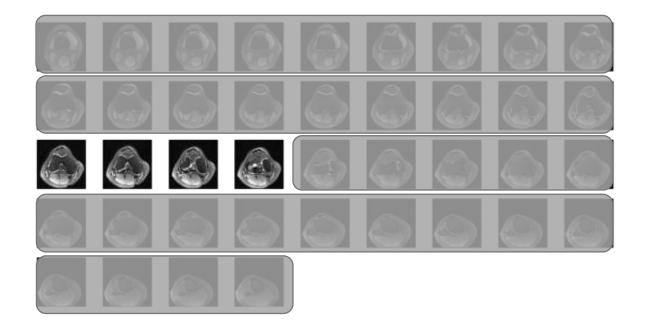
Challenges with dataset

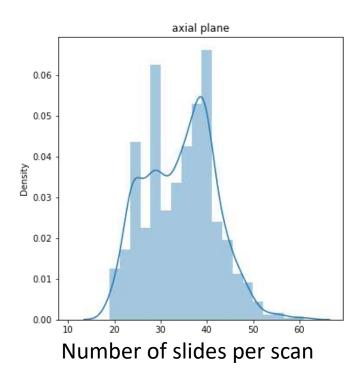
- MRI 2D multislice
 - Small gaps between slices (avoid cross-talk)



Challenges with dataset

- 1130 x s x 256 x 256 x 1
 - where 17 < *s* < 61

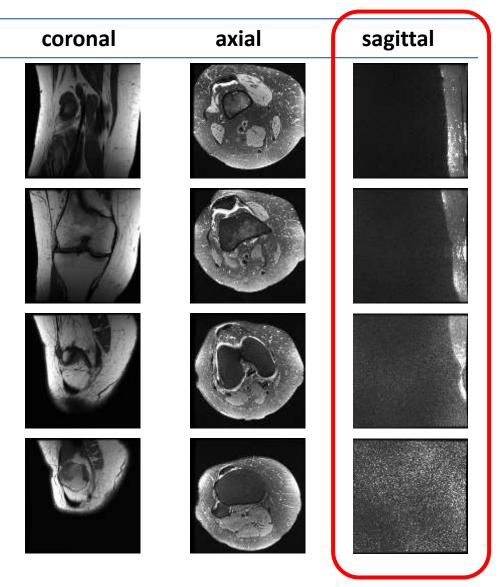




'Potentially' bad data points

- MRI 2D multislice
 - Small gaps between slices (avoid cross-talk)
 - Resolution of one plane is prioritized

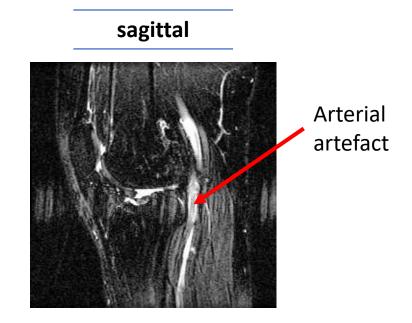
 Point-of-view (POV) of a plane is not focused.



'Potentially' bad data points

- MRI 2D multislice
 - Small gaps between slices (avoid cross-talk)
 - Resolution of one plane is prioritized

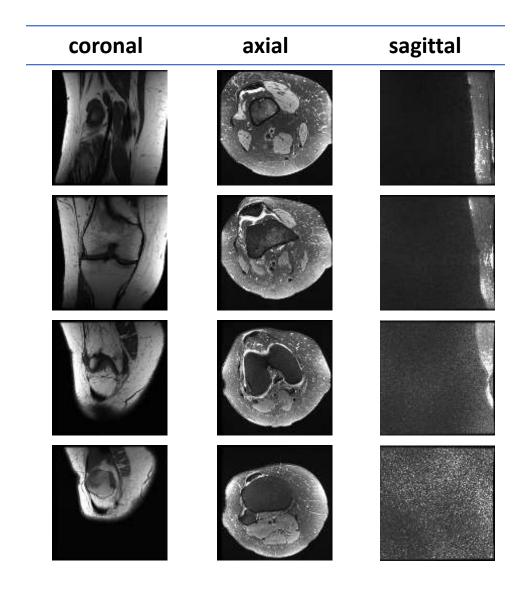
'Flow' artefacts in some images



Challenges with dataset

Hypotheses:

- Coronal or axial planes were prioritised during scanning
- Most of the meniscus tears were radial tears (best viewed in axial plane)
- Ensure root attachment of the meniscus (best viewed in coronal plane)

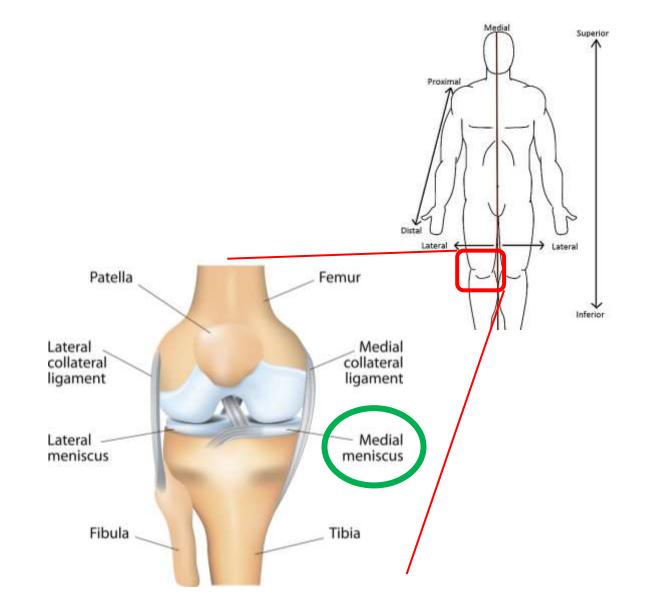


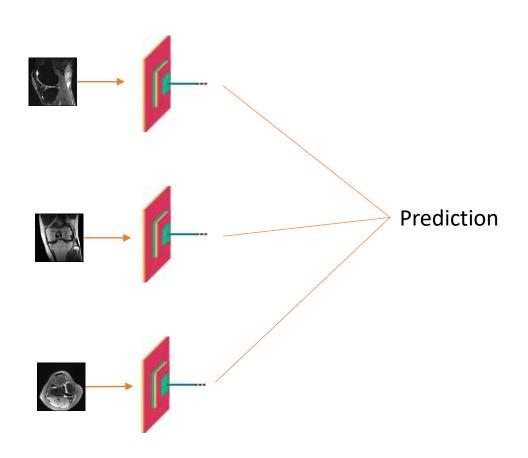
Dataset as inputs

 Extracted 3 middle images or middle image

 Images were intensity normalized. No colour was added.

 No shear, rotation, translation, etc, were performed.





 Separate models for each of the coronal, axial and sagittal planes was built.

• Metric:

- Accuracy
- Precision

Models - summary

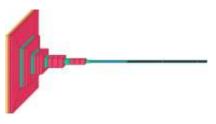
All models	
ResNet50	
VGG16	
Custom model (based on AlexNet)	
Custom model (based on LeCun)	
Functional model	

- Parameters tuned:
 - kernel regularization
 - batch normalisation
 - dropout
 - early stopping
 - batch size
 - learning rate

Models	Accuracy	Precision
ResNet50		
VGG16	0.558	0.454

• Pretrained models were overfitting.





VGG16

- Possible solutions:
 - Apply data augmentation
 - Reduce architecture complexity

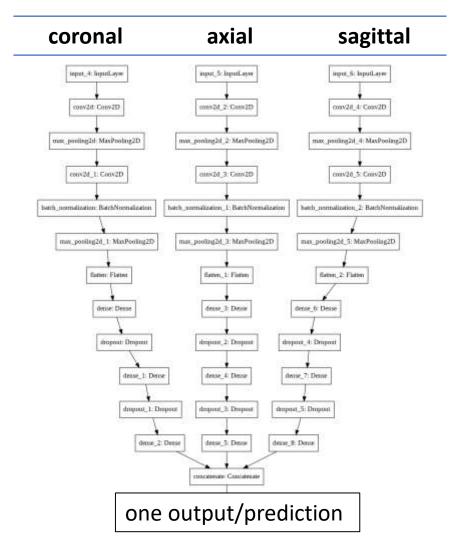
Models	Accuracy	Precision
ResNet50		
VGG16	0.558	0.454
Custom model (based on AlexNet)	0.575	0.571
Custom model (based on LeCun)	0.575	0.667

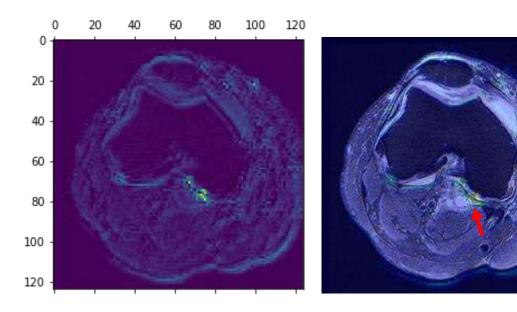
- A smaller model would not lead to better performance.
 - Constrained by images.
 - Small dataset for training.



Adapted from LeCun (LeCun et al., 1998)

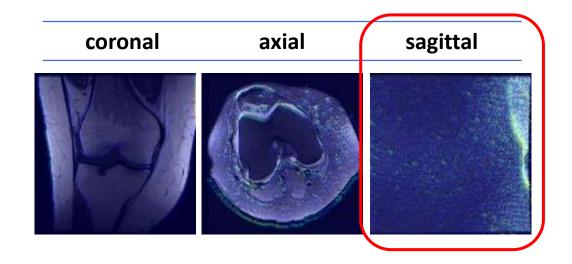
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Custom model (based on LeCun)	0.575	0.667
Functional model	0.575	1.0





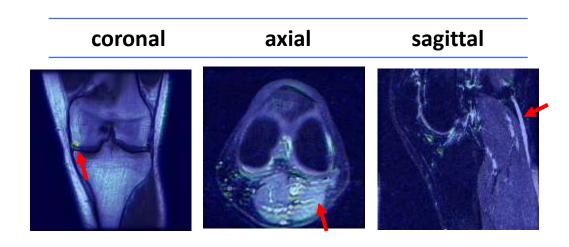
- Explainability is a major factor in healthcare.
- Classification activation mapping (CAM) was applied, to understand how the model make decisions.
- Correctly classified as meniscus tear.
- Made 'sense'.

Discussion – 'potentially' bad data points

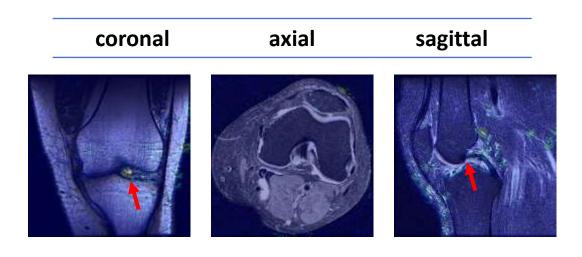


- Training set.
- Correctly trained/ classified as no meniscus tear.
- 'Learn' to look past low resolution, misaligned images.

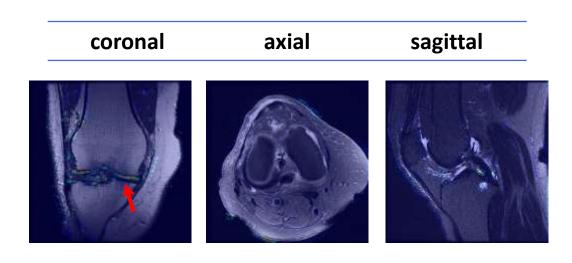
Discussion – 'potentially' bad data points



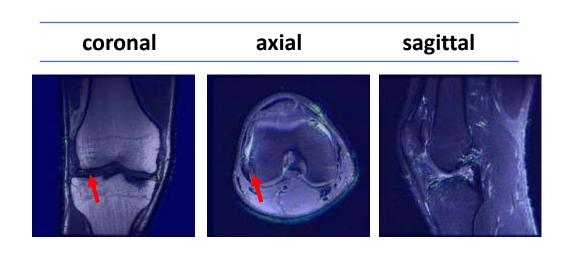
- Training set.
- Correctly trained/ classified as no meniscus tear.
- 'Learn' to look past artefacts.



- Training set.
- Correctly classified as meniscus tear.
- Looked more like an ACL tear (which is usually associated with meniscus tear).



- Training set.
- Correctly classified as meniscus tear.
- Also has an ACL tear, but only meniscus region highlighted.



- Validation set.
- Based on the axial plane, misclassified as having no meniscus tear.

Conclusion

- Functional model was selected as the 'best' model.
 - Most 'logical' model
 - Best precision score
 - 'Learn' to look past bad data points
- Since explainability is a major factor in healthcare, CAM reveals that predictions made 'sense'. Areas of interest were at regions of meniscus tears.

Recommendations

• Need for model refinement via consistent selection of clinically meaningful scans, etc.

• Out-of-sample external validation and interpretation of model.