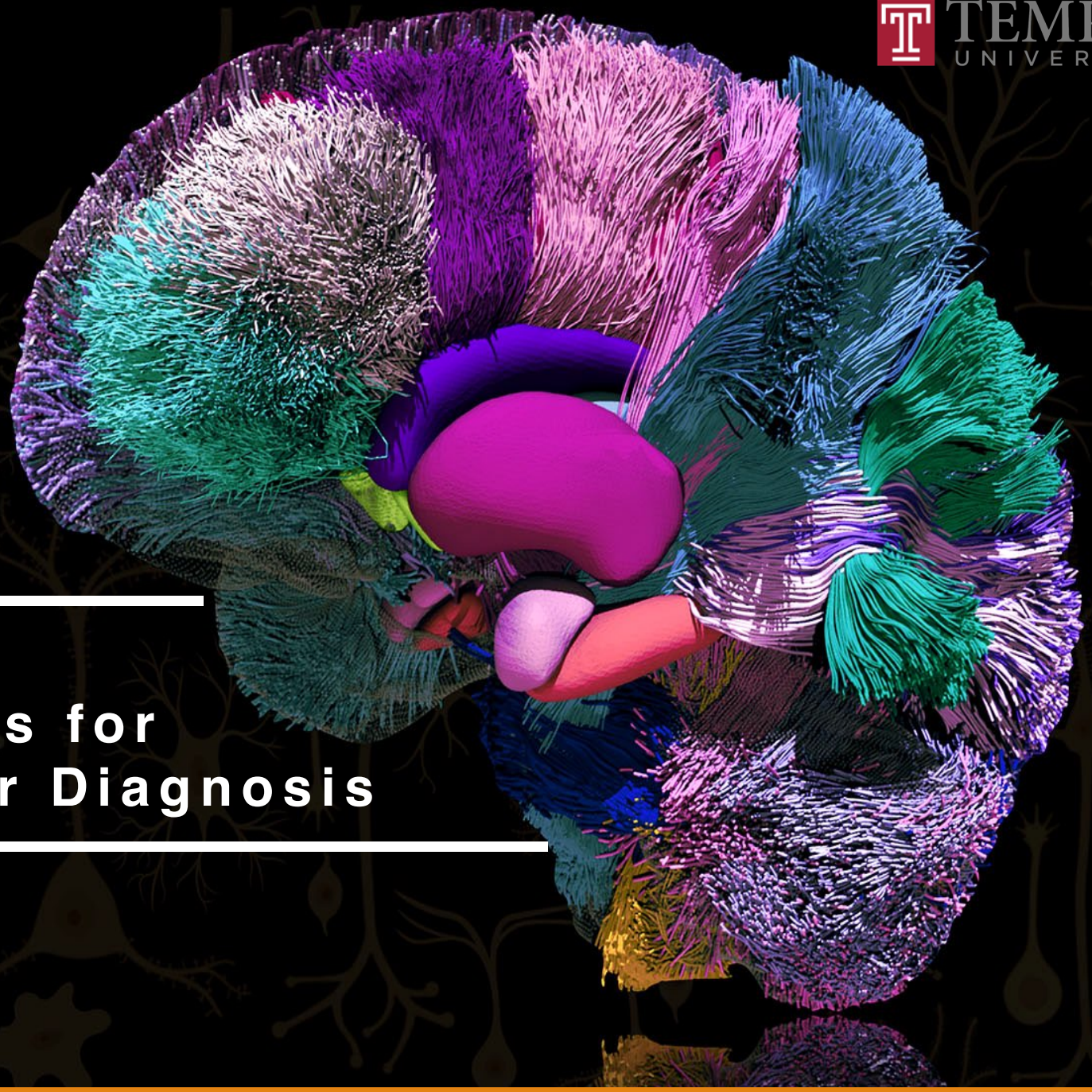
TEMPLE UNIVERSITY



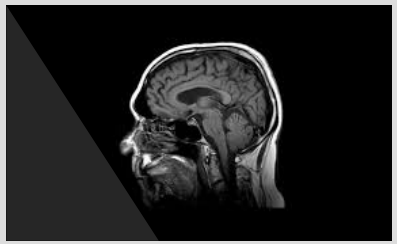
Advancements in MRI-Based Techniques for Neurological Disorder Diagnosis

Zahra Sadeghi Adl

Spring 2024

Introduction

Neurological Disorders



Magnetic Resonance Imaging

Quantitative Analysis and Machine Learning

Neurological disorders encompass a wide range of conditions affecting the nervous system, demanding accurate diagnosis for effective treatment planning and patient care.

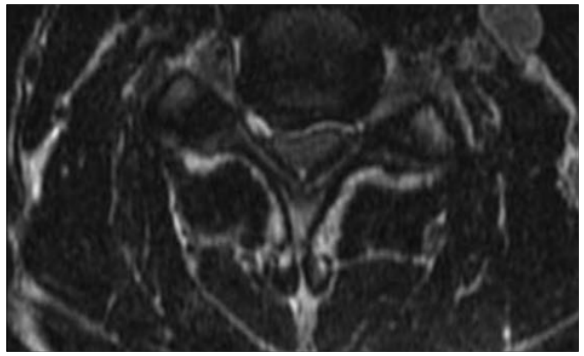
Over the past decades, magnetic resonance imaging (MRI) has transformed the landscape of neurological diagnosis.

Clinicians traditionally rely on qualitative visual inspection of MRI images, a method with inherent limitations in capturing subtle changes.

Quantitative analysis of MRI images aims to overcome these limitations by extracting precise measurements and quantitative metrics from imaging data.

Machine learning (ML) automates image analysis tasks, uncovering subtle patterns and biomarkers indicative of neurological abnormalities.

Papers

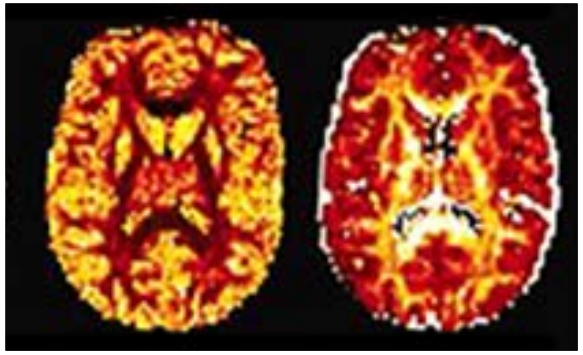


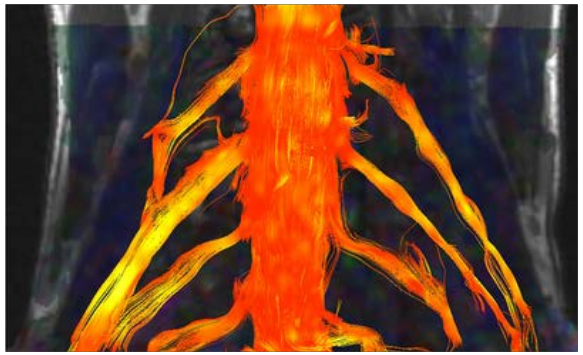
Paper 1

A deep learning model for detection of cervical spinal cord compression in MRI scans

Paper 2

Machine Learning-Based Classification of Chronic Traumatic Brain Injury Using Hybrid Diffusion Imaging

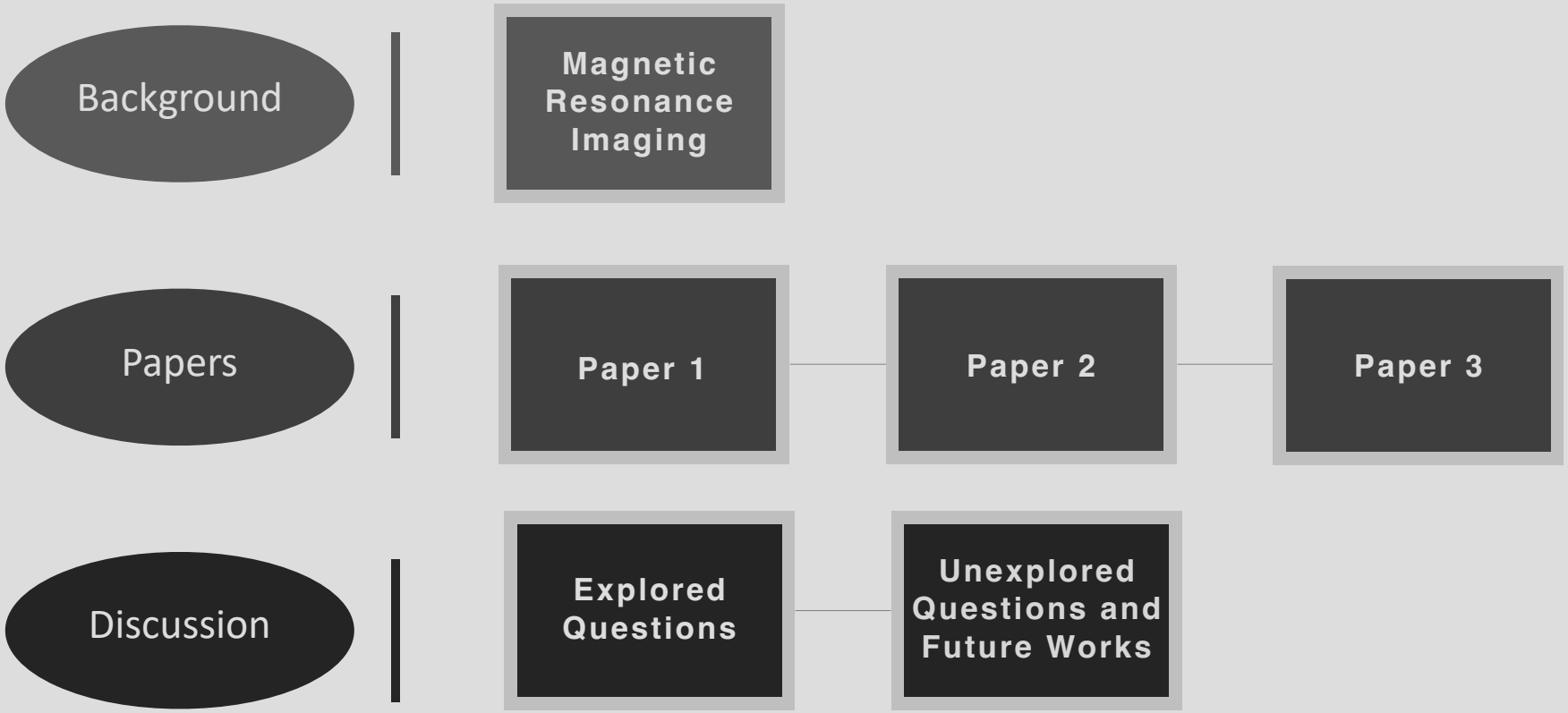




Paper 3

Quantitative Analysis in Cervical Spinal Cord Injury Patients Using Diffusion Tensor Imaging and Tractography

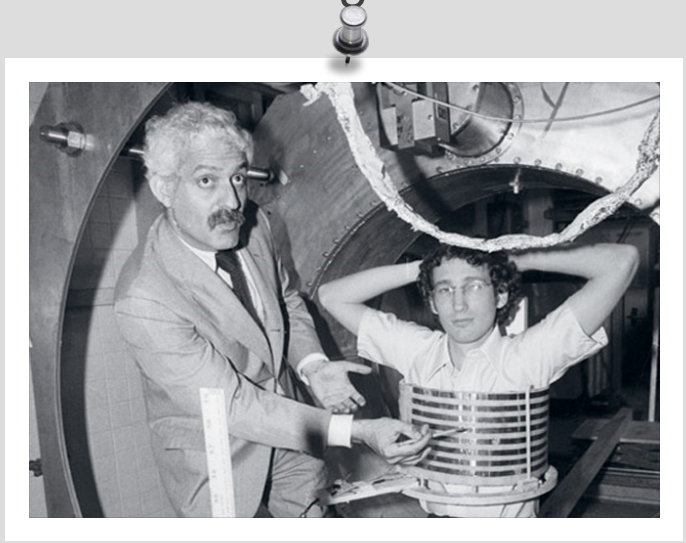
Outline


Background
Magnetic Resonance Imaging
Papers
Paper 1
Paper 2
Paper 3
Discussion
Explored Questions
Unexplored Questions and Future Works

Magnetic Resonance Imaging (1)

- Developed in the 1970s, with the first human MRI scan performed in 1977.
- Utilizes strong magnetic fields and radio waves to generate detailed images of the body's internal structures.
- Non-invasive and does not involve ionizing radiation.

Dr. Raymond Damadian's and the first full-body MRI scanner.

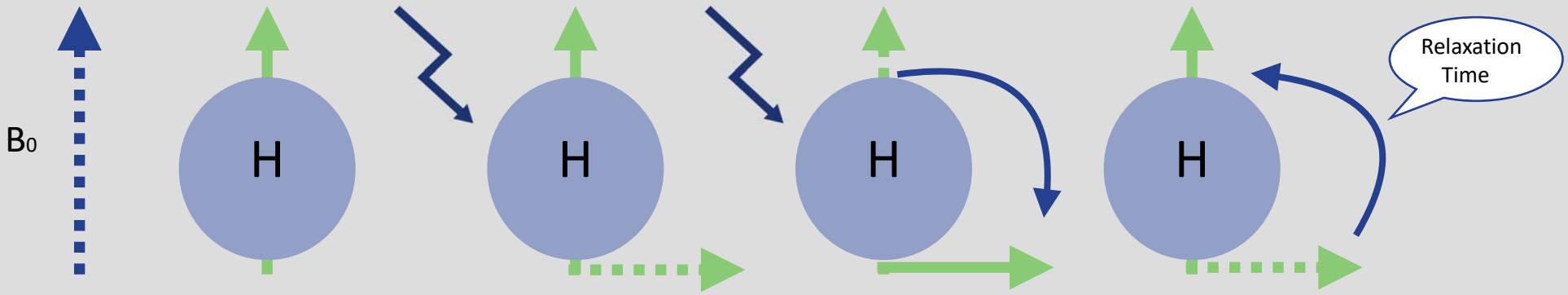


First human MRI scan

A modern MRI Scanner room

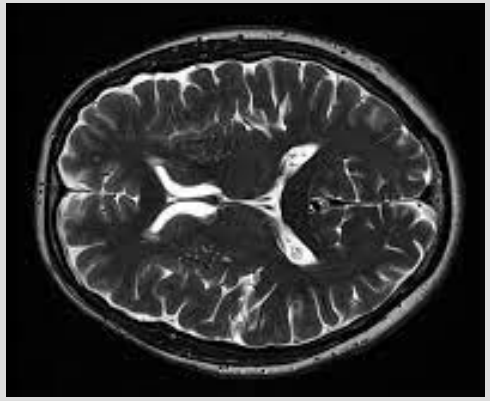
Magnetic Resonance Imaging (2)

- When the human body, rich in hydrogen atoms found in water, enters the magnetic field of MRI machine, the field aligns atoms along its direction (Longitudinal magnetic field).
- Radiofrequency pulses are then emitted, disrupting this alignment temporarily (Transverse magnetic field).
- Once these pulses cease, the atoms realign with the magnetic field, emitting energy in the form of radiofrequency signals.
- These emitted signals are detected by the MRI machine's receiver coils and processed by a computer to generate detailed images of the body's internal structures.

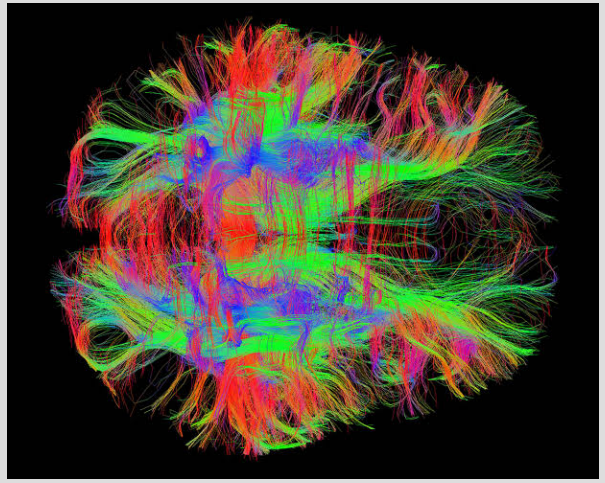


Magnetic Resonance Imaging (3)

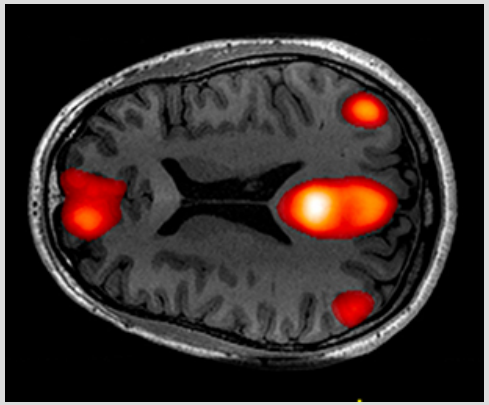
- Pulse sequences are series of radiofrequency pulses with varying parameters.
- By adjusting these parameters, pulse sequences can generate different types of MRI images with specific contrasts and features, including Structural MRI, Diffusion MRI, Functional MRI (fMRI), and more.



Structural MRI



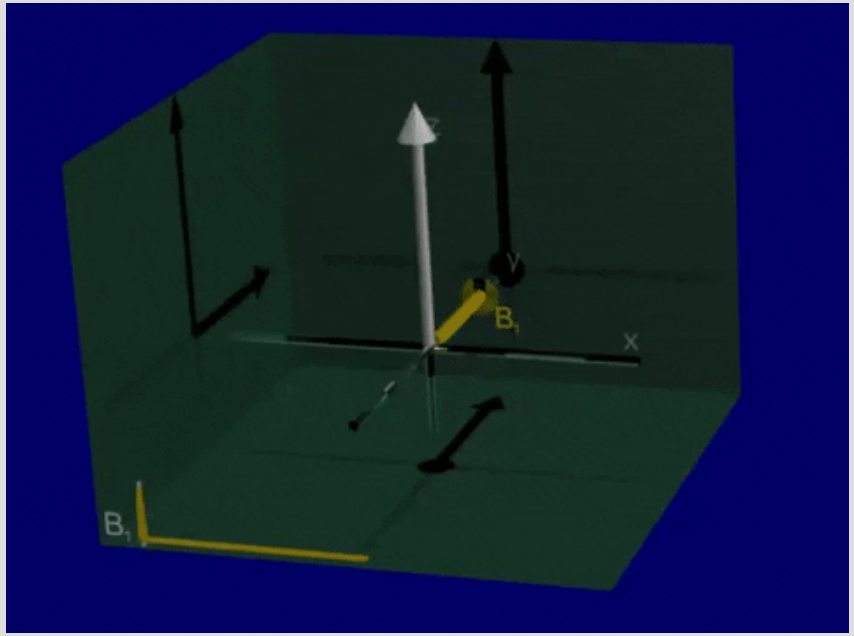
Diffusion MRI



Functional MRI

Structural MRI (1)

- Structural imaging techniques provide detailed anatomical information.
- T1 and T2-weighted images are fundamental structural imaging types used in neuroimaging, capturing different tissue contrasts based on the relaxation properties.



Relaxation (Return to equilibrium of net magnetization)

Longitudinal magnetization recovery

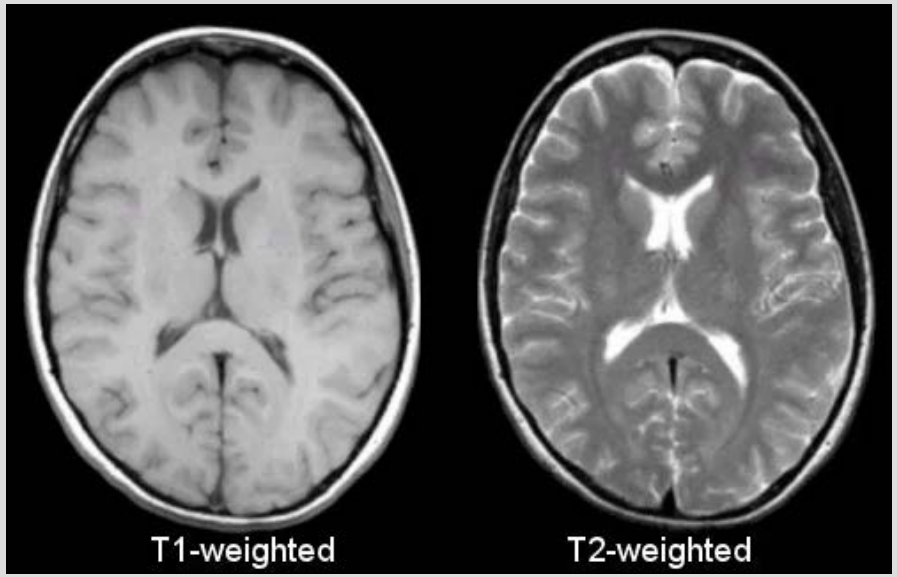
T1 relaxation refers to the process by which protons return to their equilibrium alignment with the main magnetic field.

Transverse magnetization decay

T2 relaxation is the process by which the transverse components of magnetization decay or dephase.

Structural MRI (2)

- T1-weighted images: Emphasize differences in the longitudinal relaxation time (T1) of tissues.
- T2-weighted images: Highlight differences in the transverse relaxation time (T2) of tissues.



Tissue Type	T1 Image	T2 Image
Water or Fluid Tissue	Dark	Bright
Fat Tissue	Bright	Bright
Some Bones (no free protons)	Dark	Dark

Diffusion MRI

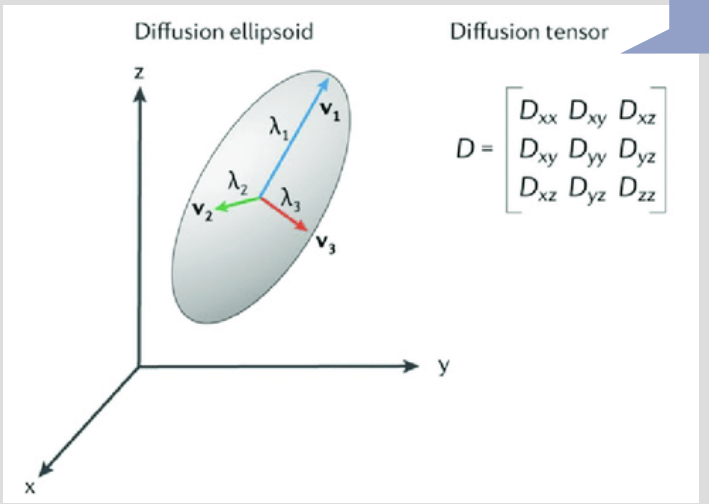
- Diffusion MRI is a specialized imaging technique that measures the random motion of water molecules within tissues, offering unique insights into tissue microstructure and connectivity.

- By quantifying the magnitude and directionality of water diffusion, Diffusion MRI provides valuable information about the organization of cellular structures in the brain and other organs.

- There are different ways to mathematically describe water diffusion, generating different types of Diffusion MRI.

Diffusion Tensor Imaging (1)

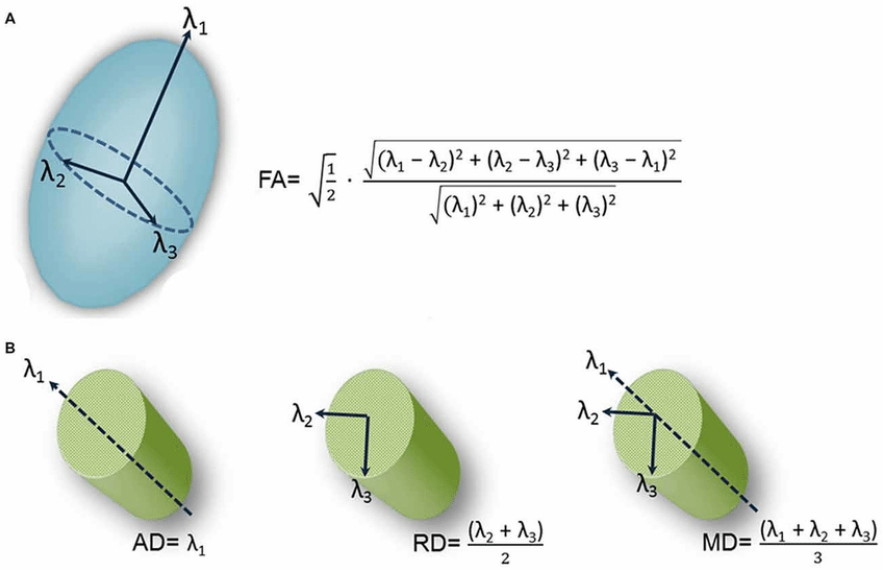
- Diffusion Tensor Imaging (DTI) is a mathematical model describing the magnitude and direction of water diffusion in three dimensions.
- DTI enables the visualization of white matter tracts
- DTI generates diffusion metrics, including Fractional Anisotropy (FA), Mean Diffusivity (MD), Radial Diffusivity (RD), and Axial Diffusivity (AD), which offer quantitative measures of tissue microstructure and integrity.

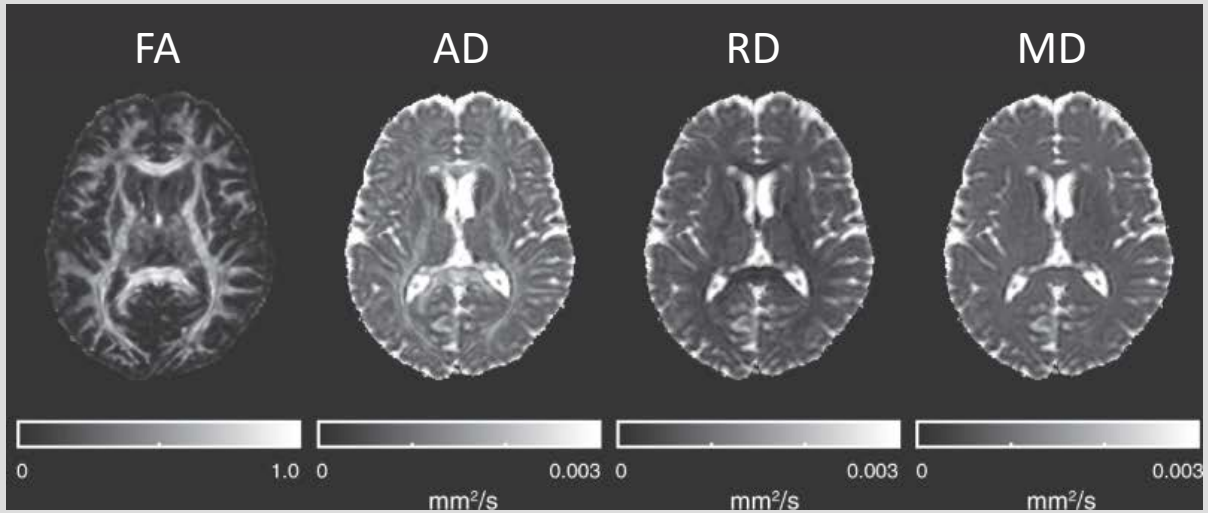


Voxel: Basic unit of a three-dimensional image obtained from MRI.

Diffusion Tensor Imaging (2)

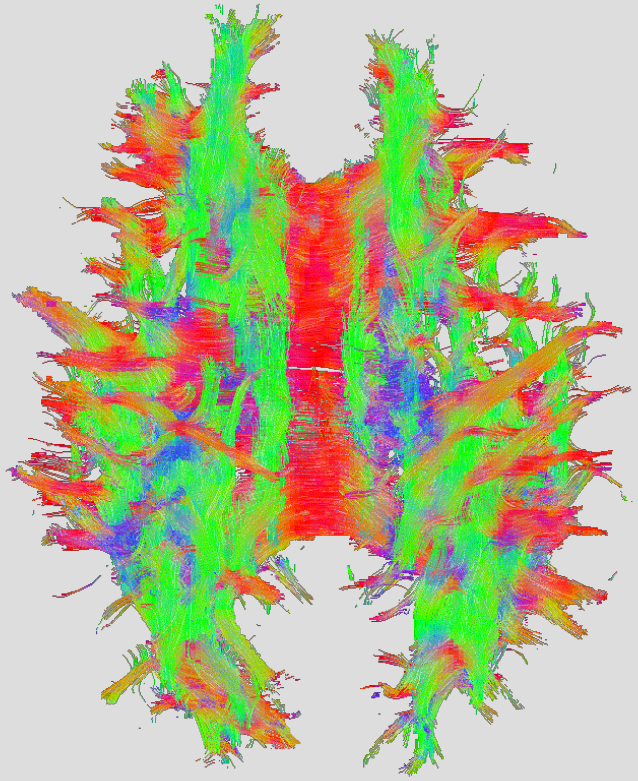
- FA: Quantifies the degree of anisotropy of water diffusion, reflecting the directionality of fiber tracts within tissues.
- MD: Average rate of water diffusion within tissues, regardless of directionality.
- RD and AD: Quantify diffusion perpendicular and parallel to the primary axis of fiber tracts.

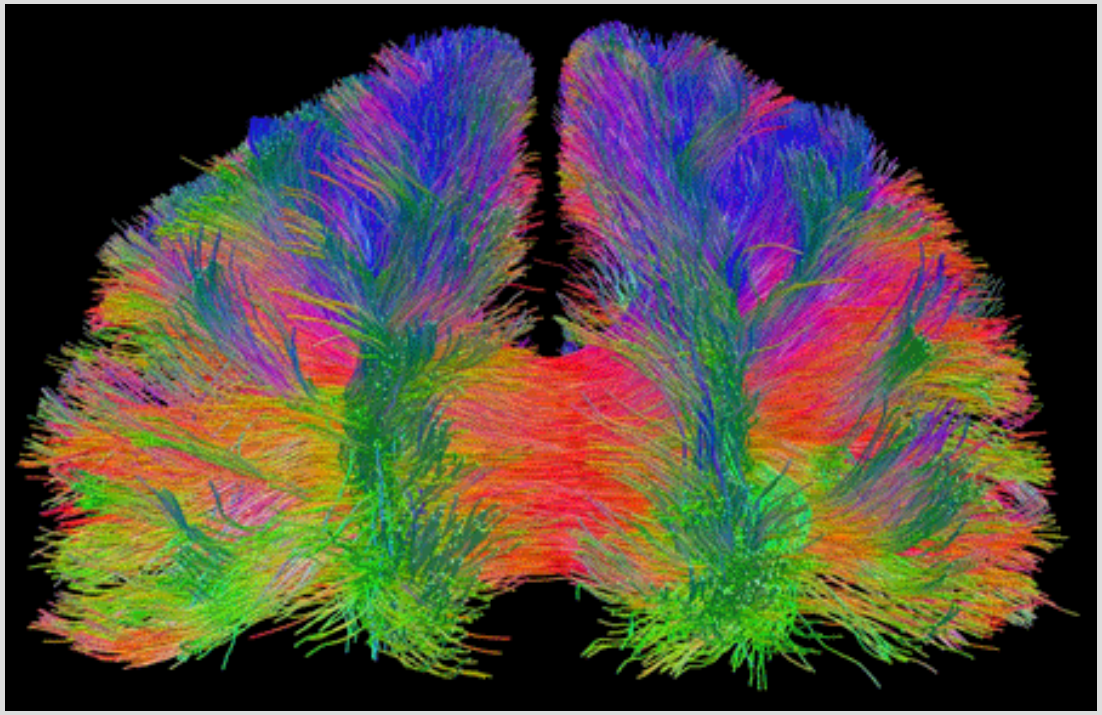




Diffusion Tensor Imaging (3)

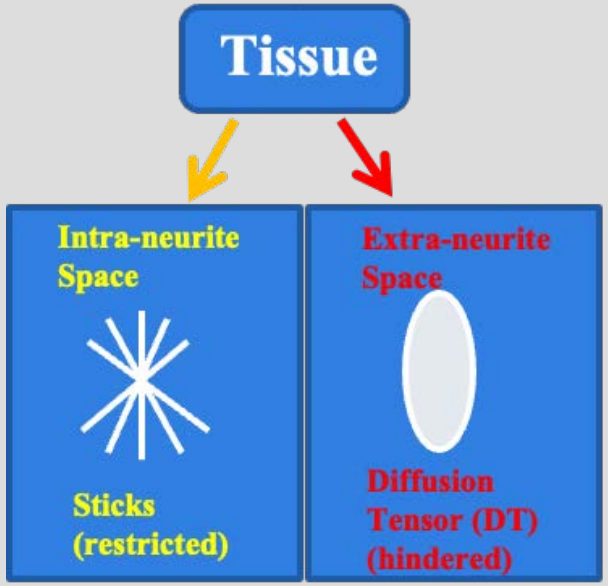
- Tractography algorithms utilize directional information of DTI to visualize and reconstruct the three-dimensional pathways of white matter tracts in the brain and spinal cord using.





Neurite Orientation Dispersion and Density Imaging (1)

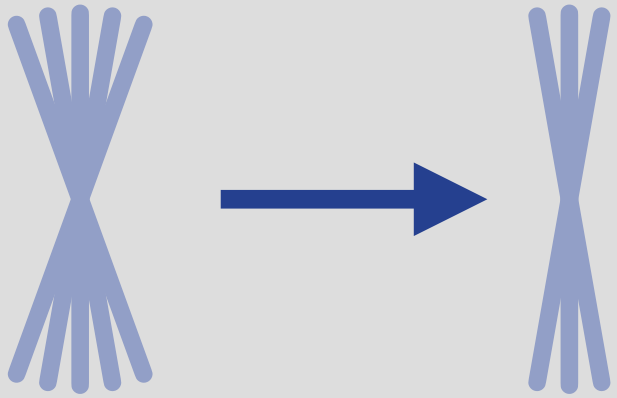
- NODDI is another advanced MRI technique that provides more detailed insights into the microstructural organization of body tissues.
- NODDI disentangles microscopic tissue compartments affecting water diffusion by modeling the density of neurites (dendrites and axons) and the dispersion of their orientations within a tissue voxel.



Neurite Orientation Dispersion and Density Imaging (2)

- The Intra-cellular Volume Fraction (VIC): Quantifies the proportion of a voxel's volume occupied by neurites.
  VIC reflects the density of neurites within a specific region, providing information about the abundance of neuronal processes in the tissue.

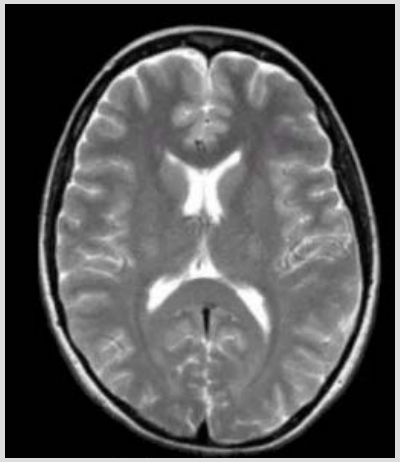
- Orientation Dispersion Index (ODI): Quantifies the dispersion of neurite orientations within a voxel. ODI measures the degree to which neurites are oriented in different directions within the voxel.



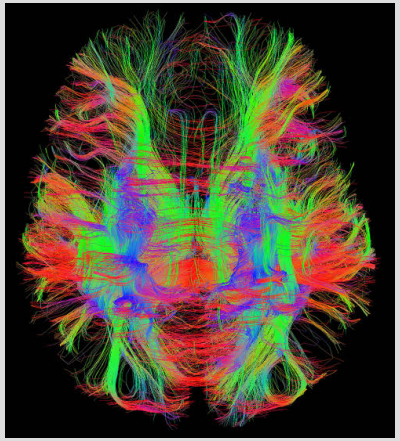
VIC Decrease
ODI Decrease

Summary

Structural



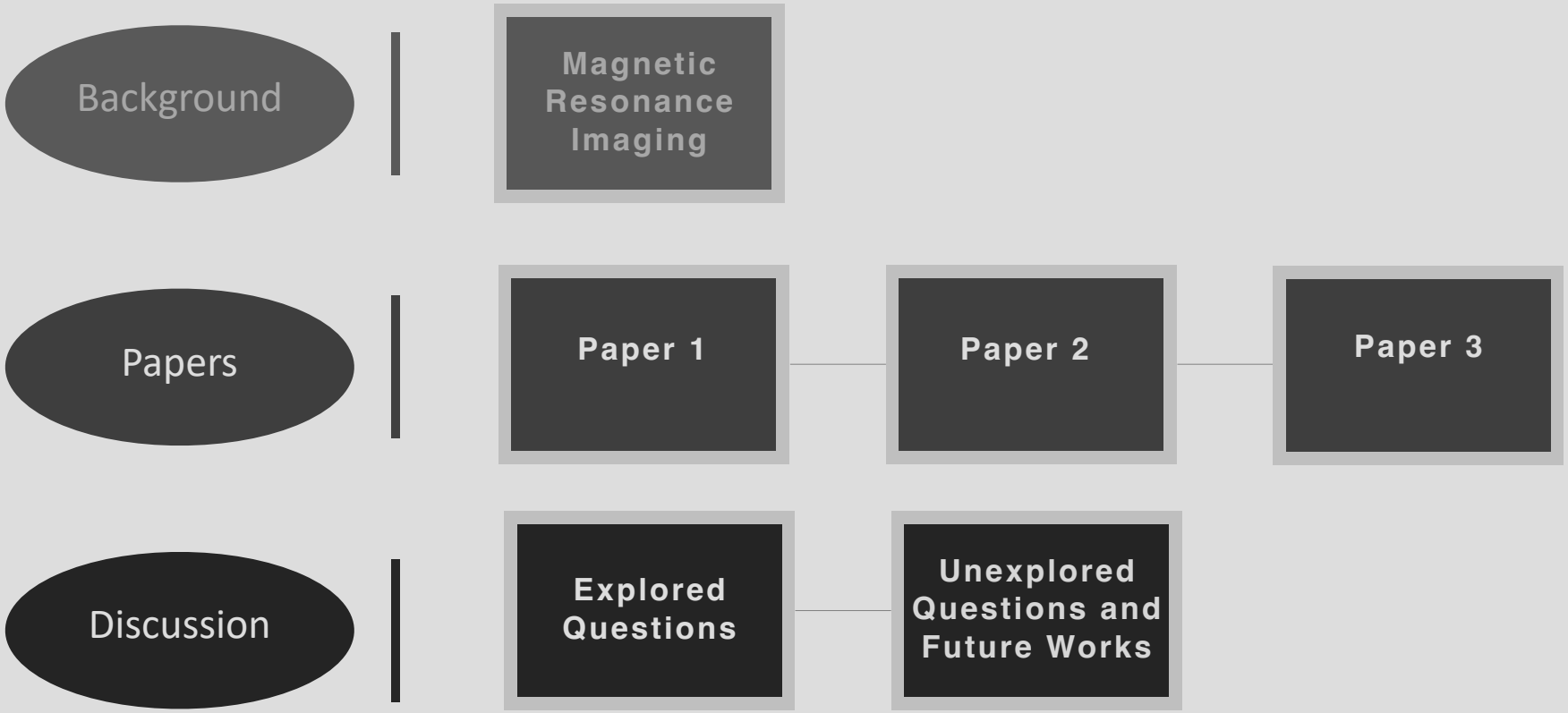
Diffusion



Technique
T1-weighted Images
T2-weighted Images

Technique	Metric	Measurement
DTI	Fractional Anisotropy (FA)	Degree of diffusion directionality
	Mean Diffusivity (MD)	Average diffusion magnitude
	Radial Diffusivity (RD)	Diffusion magnitude perpendicular to primary axis
	Axial Diffusivity (AD)	Diffusion magnitude along primary axis
NODDI	The Intra-cellular Volume Fraction (VIC)	Fraction of intracellular water volume for a given voxel
	Orientation Dispersion Index (ODI)	Angular variation of neuritis orientation

Outline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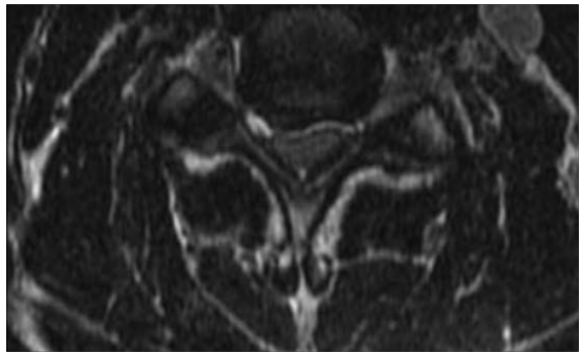

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Paper 2

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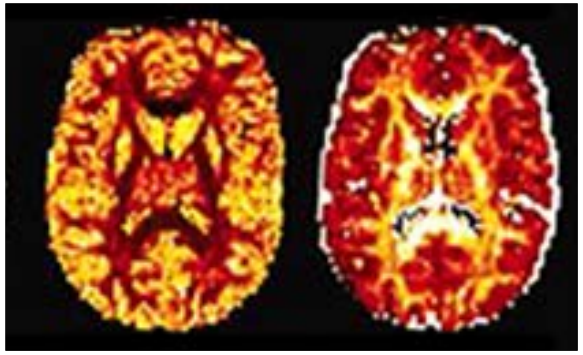

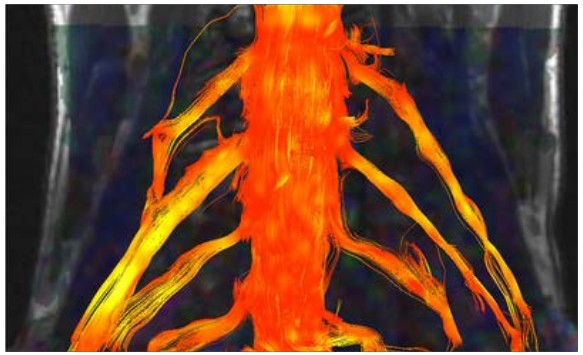

Paper 3

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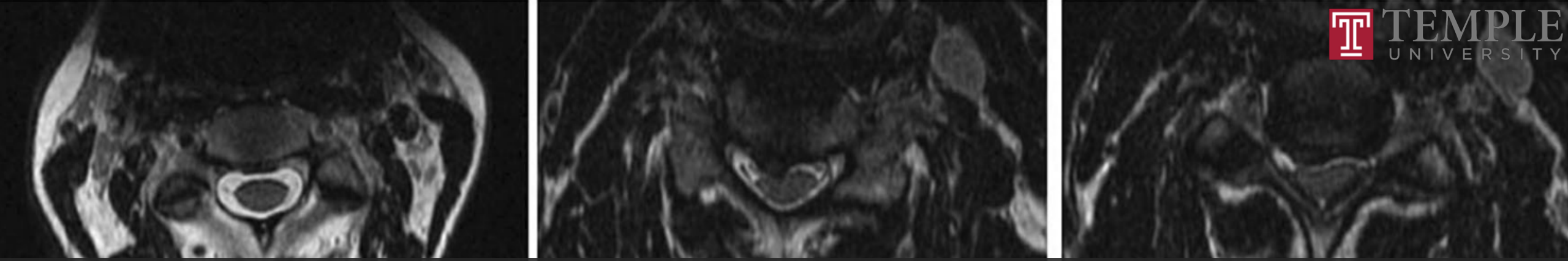


Paper 1

A Deep Learning Model for Detection of Cervical Spinal Cord Compression in MRI Scans

Objective

Develop and validate a deep learning model for the detection of Degenerative Cervical Myelopathy (DCM) using MRI scans.

Subjects

A total of 289 patients with DCM.

Data Type

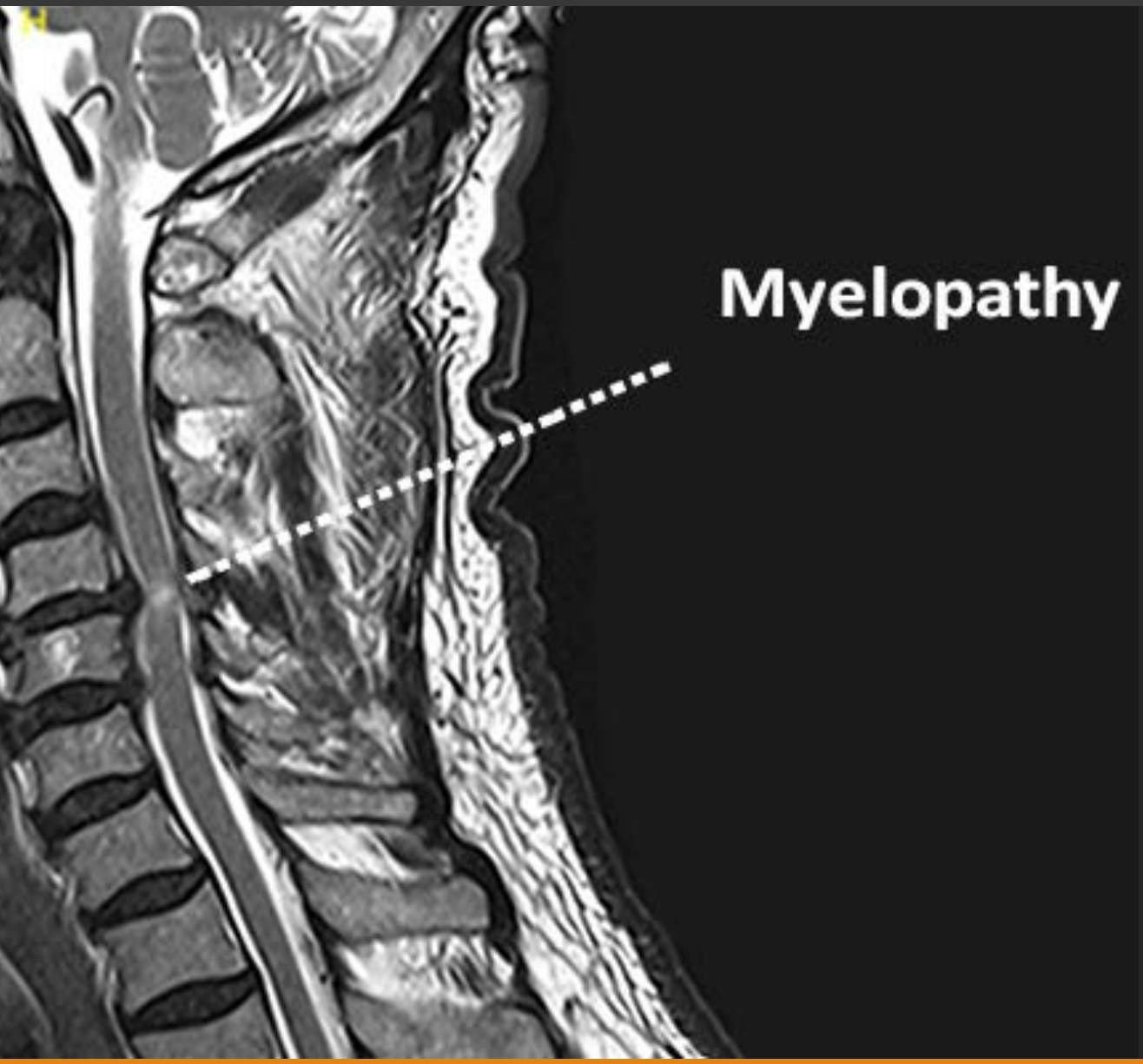
Structural (T2-weighted) MRI scans of patients undergoing surgery for DCM

Method

Deep convolutional neural network (CNN), ResNet50, was trained using axial images, to classify compressed and non-compressed cervical spinal cord images.

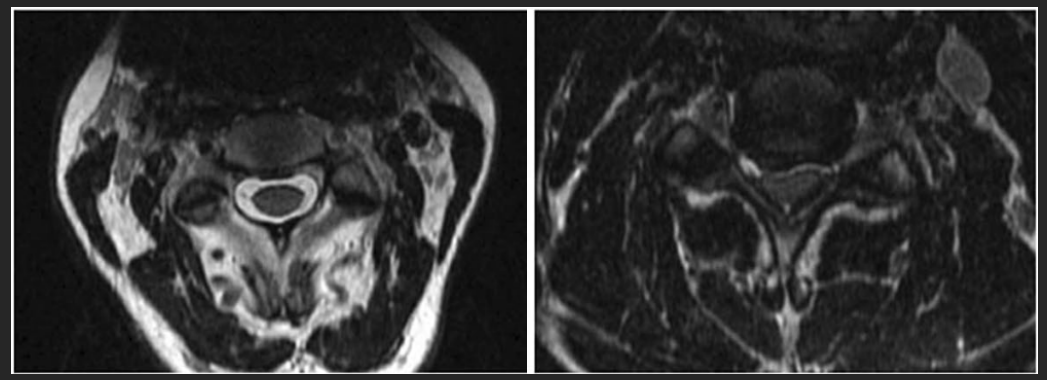
Merali, Z., Wang, J. Z., Badhiwala, J. H., Witiw, C. D., Wilson, J. R., & Fehlings, M. G. (2021). A deep learning model for detection of cervical spinal cord compression in mri scans. Scientific reports, 11 (1), 10473

A Deep Learning Model for Detection of Cervical Spinal Cord Compression in MRI Scans



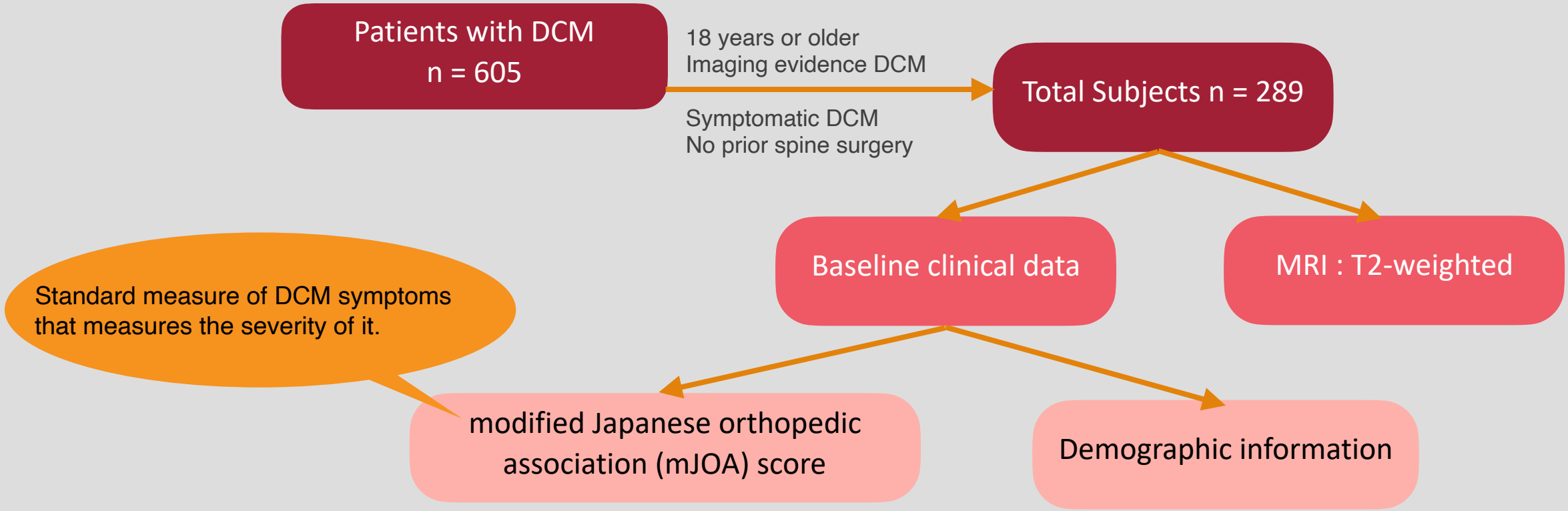
Degenerative Cervical Myelopathy

- A common condition characterized by compression of the spinal cord in the neck region (cervical spine)
- Caused by degenerative changes, leads to narrowing of the spinal canal and compression of neural structures.



Normal Cervical Spine | Compressed Cervical Spine

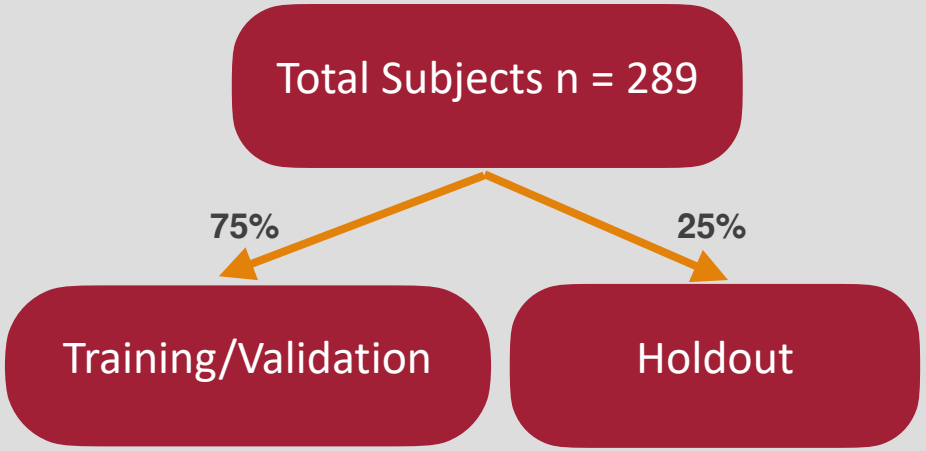
Subjects


Patients with DCM
n = 605
18 years or older
Imaging evidence DCM
Symptomatic DCM
No prior spine surgery
Total Subjects n = 289
Baseline clinical data
MRI : T2-weighted
Standard measure of DCM symptoms that measures the severity of it.
modified Japanese orthopedic association (mJOA) score
Demographic information

Subjects

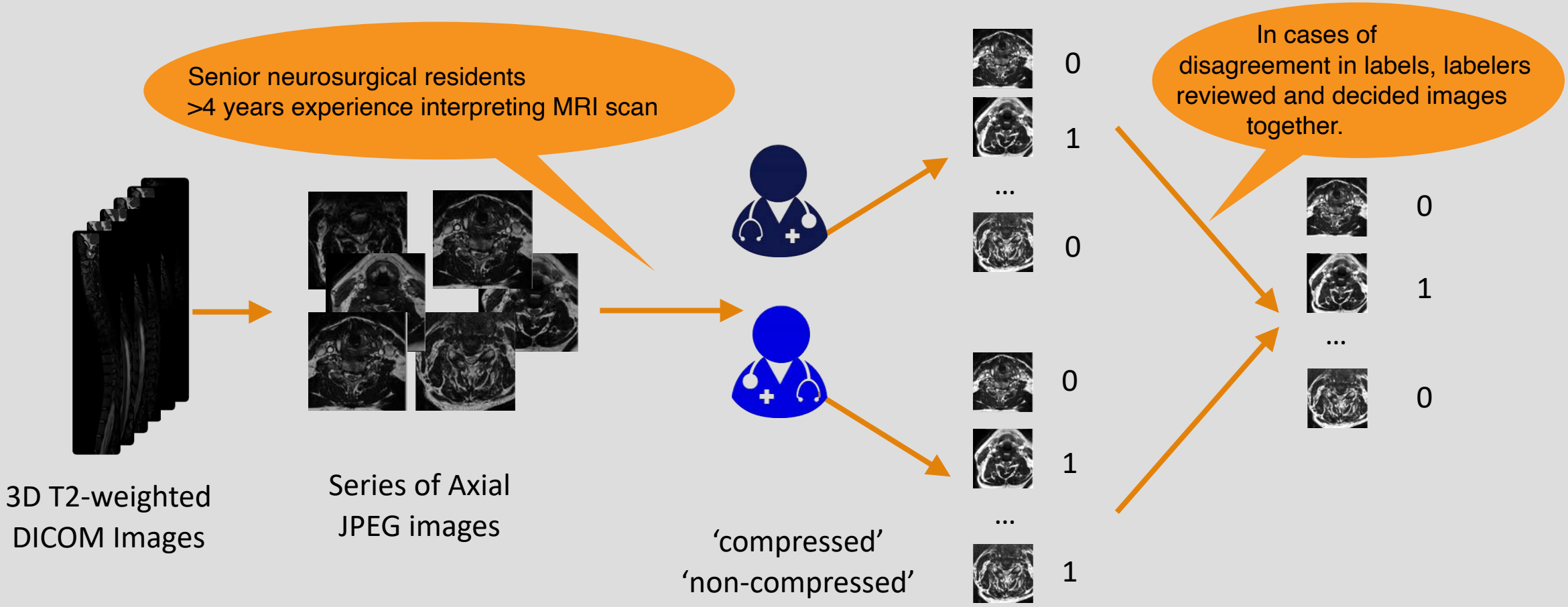
Dataset was divided into training/validation and holdout datasets.

Used t-tests to compare training/validation and holdout dataset.



	Training/ Validation (n= 201)	Holdout (n=88)	P-value
Age (median)	55	56	0.65
Gender (male)	63%	66%	0.53
Baseline mJOA (median)	13	13	0.72

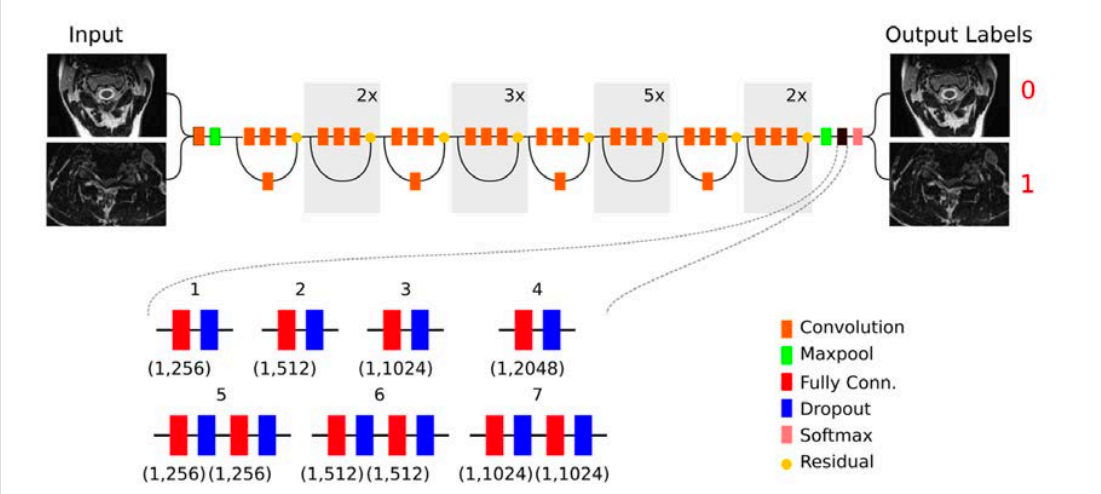
Labeling

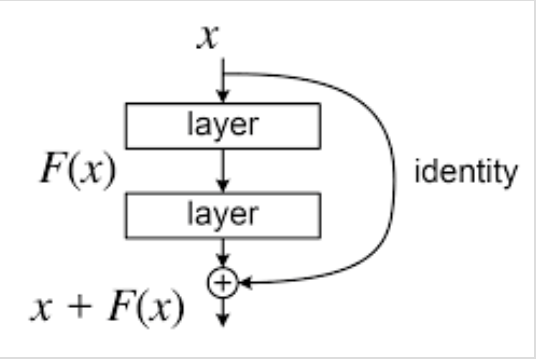

Senior neurosurgical residents
>4 years experience interpreting MRI scan
3D T2-weighted
DICOM Images
Series of Axial
JPEG images
'compressed'
'non-compressed'
0
1
...
0
0
1
...
1
In cases of
disagreement in labels, labelers
reviewed and decided images
together.
0
1
...
0

Model

Pre-trained ResNet50 was used for classification task.

- ResNet, short for Residual Network, is a type of deep neural network architecture.
- Introduced by Microsoft Research in 2015, it addressed the problem of vanishing gradients in deep networks.
- Traditional deep networks suffer from the vanishing gradient problem, where gradients diminish as they propagate backward through many layers, hindering training.
- ResNet introduces skip connections, or shortcuts, that allow gradients to bypass several layers, mitigating the vanishing gradient problem.





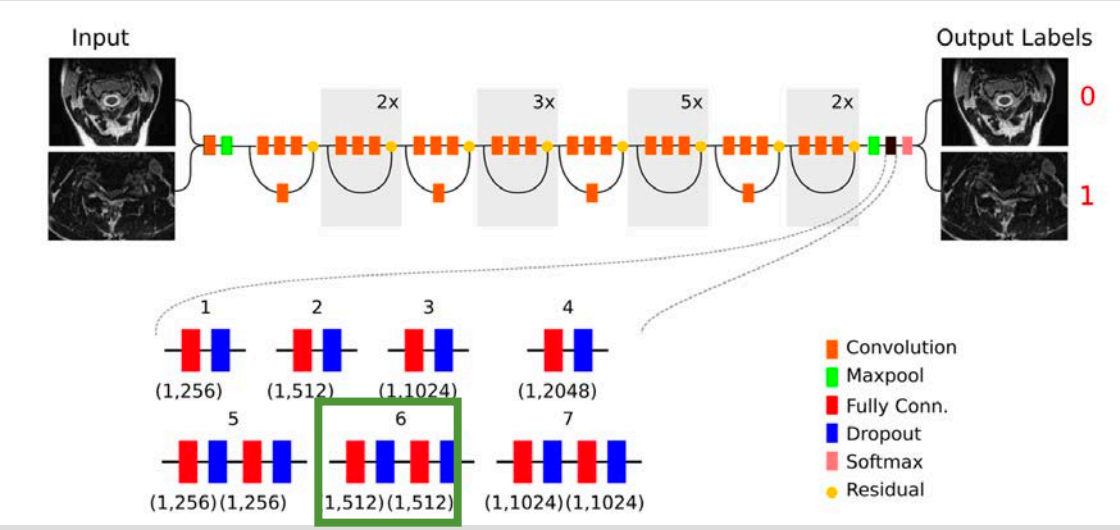
Model Selection

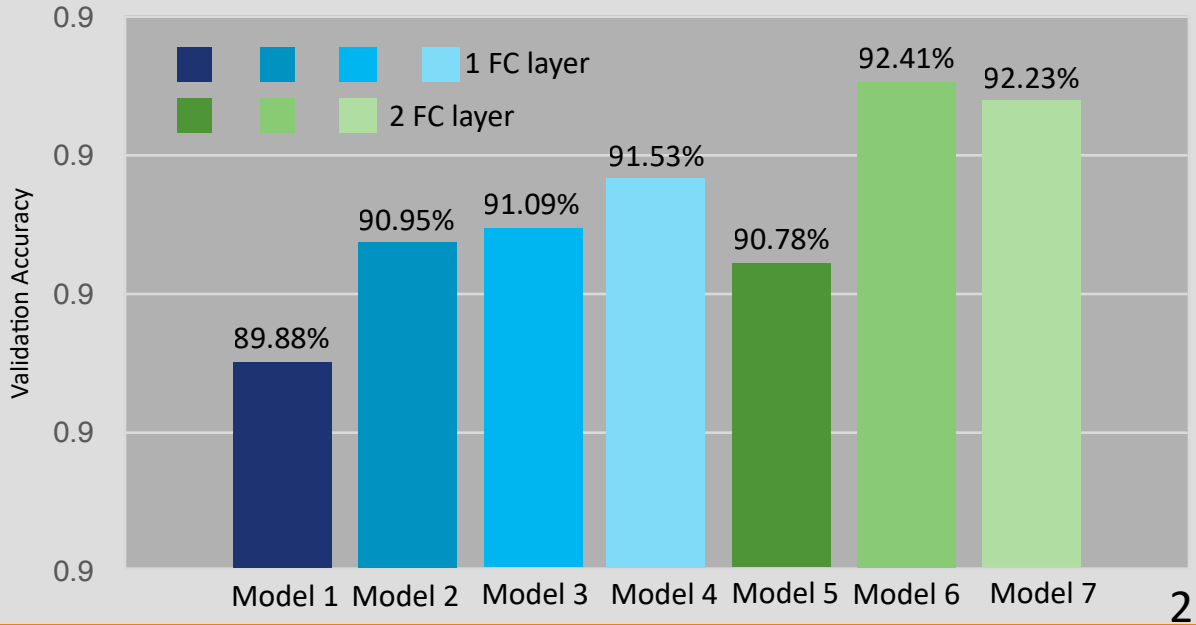
The model's initial weights were transferred from the pre-trained weights developed on ImageNet.

The fully connected layers were replaced by one or two fully connected layers, with 256 to 2048 neurons, with or without dropout layers, with randomly initialized weights.

Dropout layers were employed to mitigate overfitting during training.

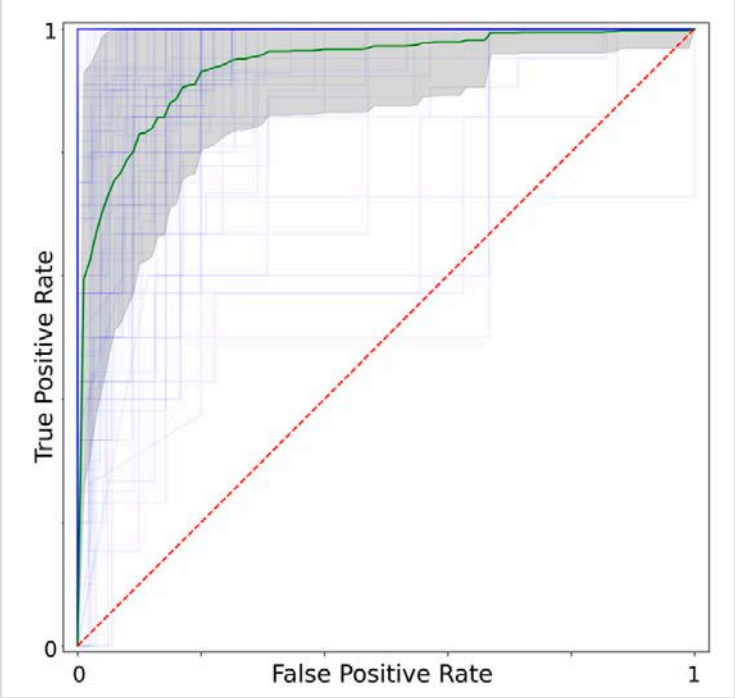
The best performing model architecture was evaluated on the holdout dataset.





A Deep Learning Model for Detection of Cervical Spinal Cord Compression in MRI Scans

Results



For each patient in the holdout dataset the classification output of the deep learning model for each slice was compared to the class labels.
A ROC curve and AUC metric was generated for each patient by comparing the predicted and actual classes for each slice.
Sensitivity of 0.88, Specificity of 0.89, and f1-score of 0.82.

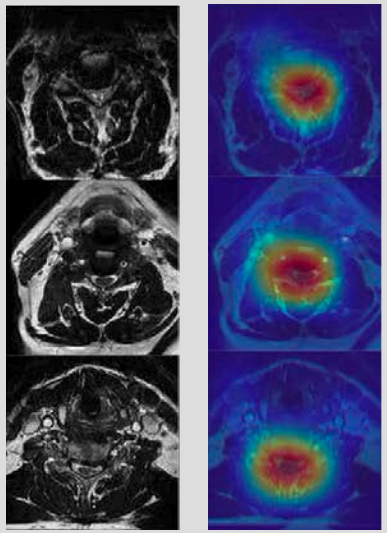
	Area Under the Curve (SD)	p-value
Entire Holdout Dataset (n = 88)	0.94 (0.08)	
Age (years)		
< 40 (n = 9)	0.88 (0.14)	0.12
40–65 (n = 63)	0.95 (0.06)	0.78
> 65 (n = 16)	0.92 (0.09)	0.45
mJOA		
18 (n = 2)	1.00 (0)	0.94
15–17 (n = 22)	0.96 (0.04)	0.67
12–14 (n = 39)	0.92 (0.09)	0.62
< 12 (n = 25)	0.95 (0.07)	0.77
MRI Scanner Manufacturer		
GE Medical Systems (n = 52)	0.94 (0.07)	0.82
Siemens (n = 25)	0.93 (0.06)	0.71
Philips Medical Systems (n = 11)	0.95 (0.08)	0.74

Results

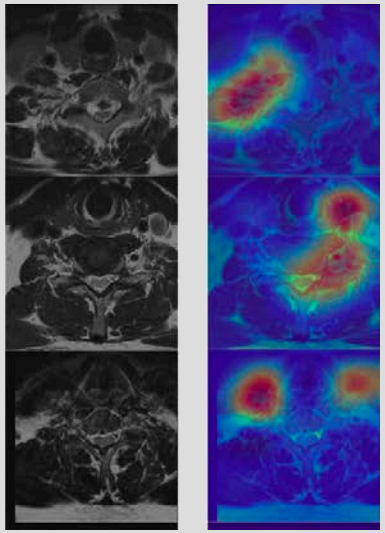
Class activation maps were generated for both correctly classified (true positives) and incorrectly classified (false negatives) example images.

- Class Activation Map (CAM) is a visualization technique used in deep learning to interpret and understand the decisions made by convolutional neural networks (CNNs) for image classification tasks.
- Provides a spatial map highlighting the regions of an input image that contribute most significantly to the prediction of a particular class by the CNN.

True Positive



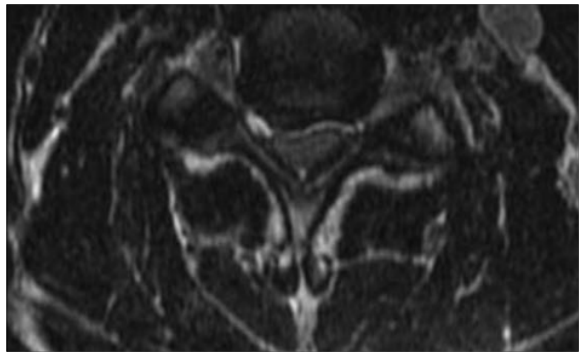
False Negative



Conclusion

- The study focused on training and testing an image-based model for detecting spinal cord compression in cervical spine structural MRI scans.
- Used series of 2D structural images to identify compressed and non-compressed parts of the spinal cord in DCM patients.
- High performance was achieved, with an AUC of 0.94 on a heterogeneous patient population.

Papers



Paper 1

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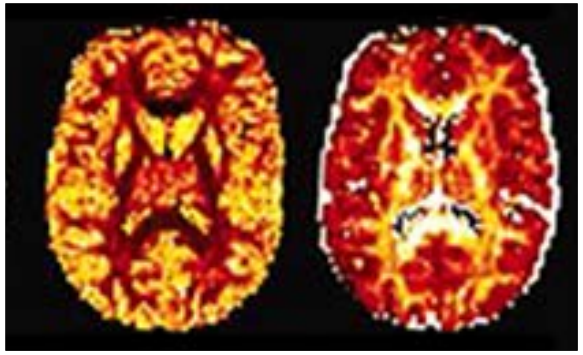
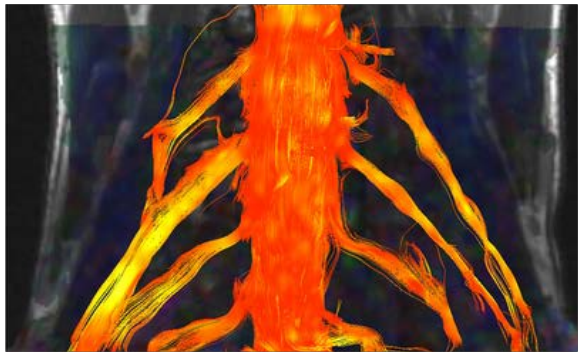
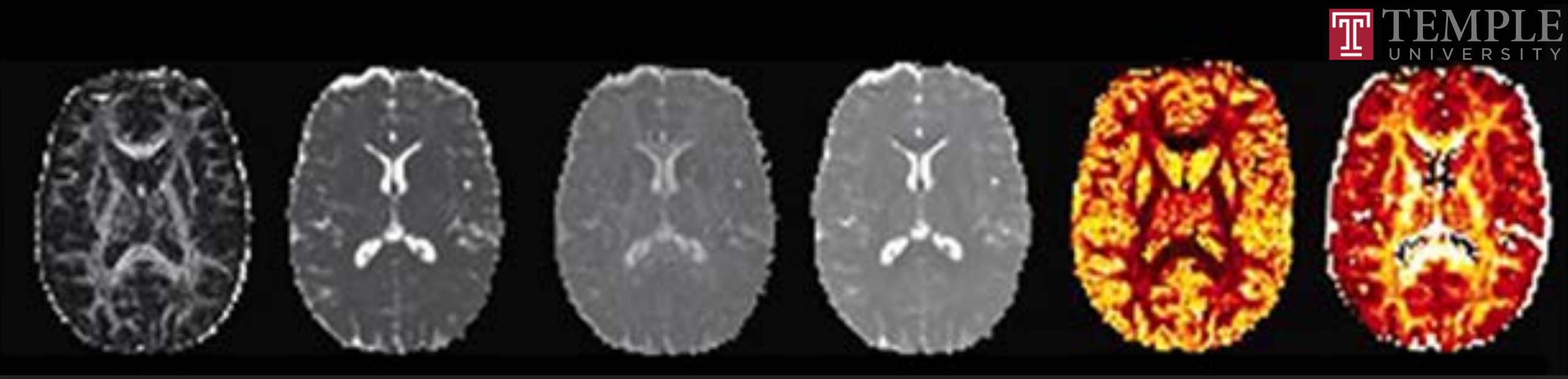




Paper 3

Quantitative Analysis in Cervical Spinal Cord Injury Patients Using Diffusion Tensor Imaging and Tractography



Paper 2

Machine learning-based classification of chronic traumatic brain injury using hybrid diffusion imaging

Objective

Analyze the ability of data-driven analysis of DTI and NODDI to develop biomarkers to infer symptom severity of Traumatic brain injury and determine whether they outperform conventional T1-weighted imaging.

Subjects

A total of 59 subjects experiencing chronic symptoms caused by a mild traumatic brain injury.

Data

DTI, NODDI and structural T1-image was obtained for all subjects.
Clinical assessments, the trail making test, were performed on the same day as the imaging study.

Method

Using decision tree and K-NN models for feature selection and classification model to predict clinical outcomes of cTBI using DTI, NODDI and T1-images.

Muller, J. J., Wang, R., Milddleton, D., and others (2023). Machine learning-based classification of chronic traumatic brain injury using hybrid diffusion imaging. Frontiers in Neuroscience, 17 , 1182509.

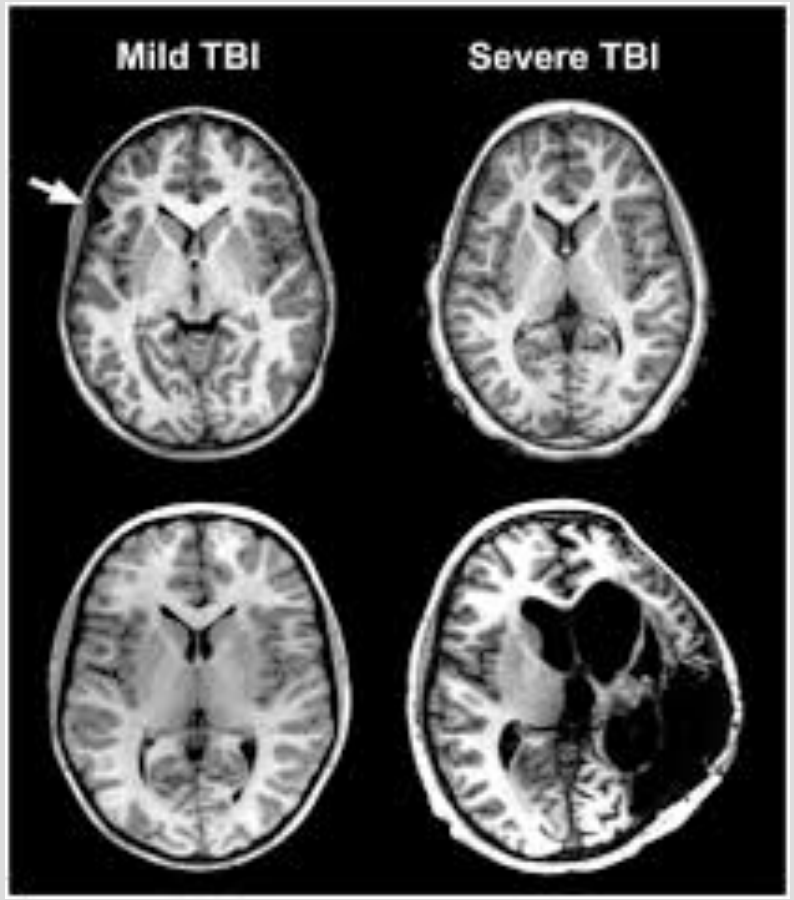
Traumatic brain injury

Traumatic Brain Injury (TBI) is a severe medical condition resulting from sudden trauma or impact to the head, leading to the disturbance of normal brain function.

It has contributed to approximately 1 million deaths in the United States over the last two decades.

Conventional T1-weighted imaging often appears normal in cases of mild-to-moderate injury.

To enhance diagnosis and monitor both acute and chronic effects of TBI, researchers are actively investigating advanced neuroimaging biomarkers.

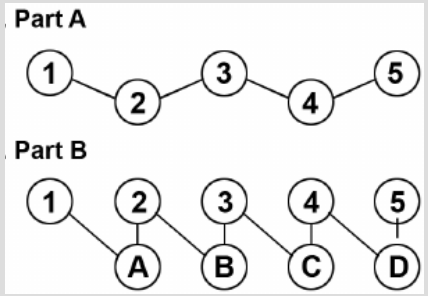


Subjects

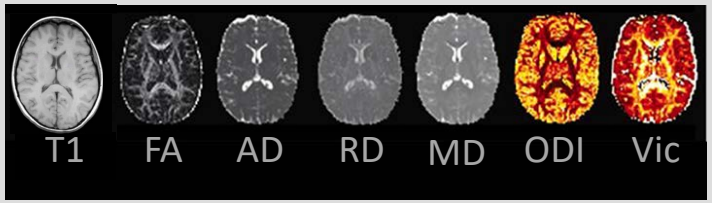
59 subjects with mild traumatic brain injury

Clinical Assessment
Trail Making (A, and B) test

MRI: DTI, NODDI and T1-weighted images



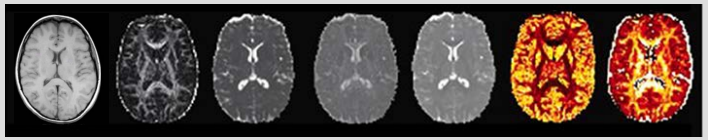
Stop timing when the Trail is completed, or when maximum time is reached (150 seconds = 2.5 min)



Labeling

Subjects were classified as having favorable or unfavorable outcomes in each the tested outcomes, depending on whether their individual score was lower or higher than the mean value of the entire cohort.

Data



Label

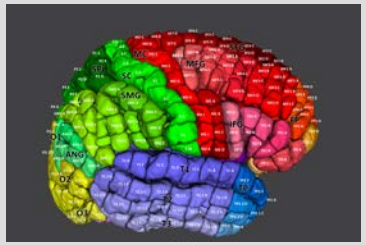
	Favorable
A	
B	

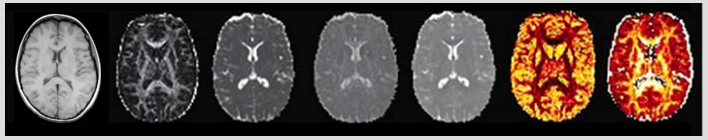
	All patients	Favorable outcome	Unfavorable outcome
Trail making A (sec)	29.9	22.9 (n=40)	43.9 (n=19)
Trail making B (sec)	67.1	52.9 (n=38)	92.7 (n=21)

Pre-Processing

Segmentation of anatomical regions was done using Johns Hopkins University white matter tractography atlas, which divides the brain into 20 regions.

Within each segmented region, DTI, NODDI and T1 parameters were computed.





	T1	FA	AD	RD	MD	ODI	Vic
R1							
R2							
.							
.							
.							
R20							

Model

ML-Based Classification Pipeline:

Developed using a feature selection decision tree followed by a K-NN model.

Decision trees generated for each task and parameter using the Gini Impurity method.

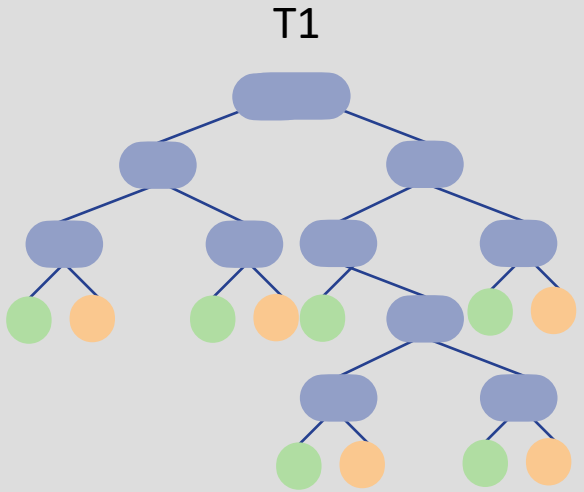
From the trained trees, the six brain regions with the lowest impurity scores were selected.

These selected regions were used for classification task using KNN model .

	T1	FA	AD	MD	RD	Vic	ODI
R1							
R2							
.							
.							
.							
R20							

	Favorable
A	
B	

Trail A

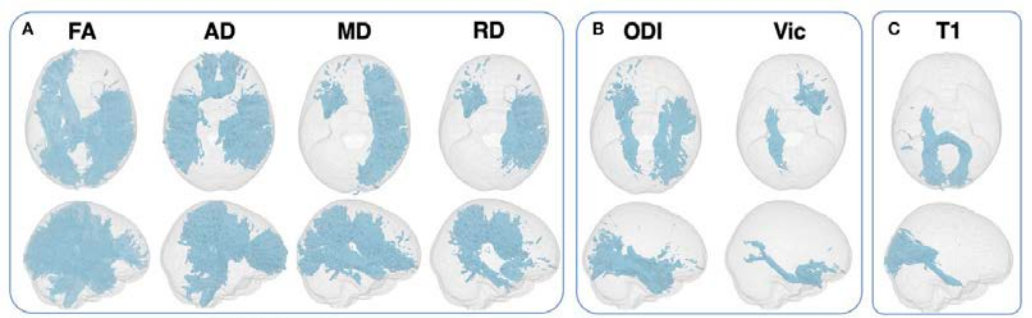


	T1	FA	AD	RD	MD	ODI	Vic
SR1							
SR2							
⋮							
SR6							

Model

Decision Tree and K-NN

Then using the selected regions of the brain and a K-NN model (K=10) the classification for Trail A and B is done.



Feature ranking results for DTI (A), NODDI (B), and T1 (C) regions. Features are displayed if they were ranked as significant for both trail making A and B.

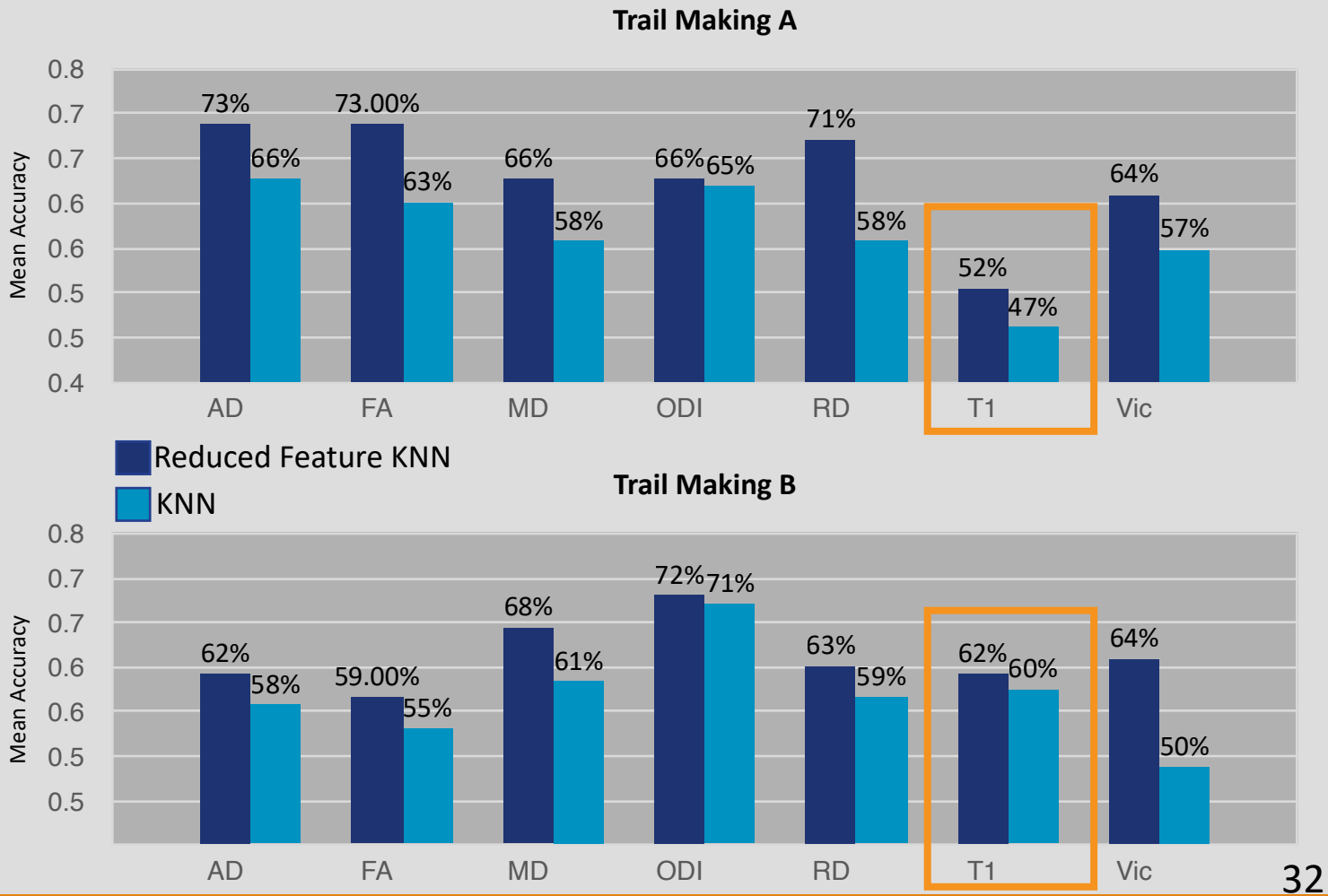
Metric	Test	Selected features
T1	Trail Making A	Cingulum (cingulate gyrus) L, Cingulum (cingulate gyrus) R, Cingulum (hippocampus) L, Forceps major, Inferior fronto-occipital fasciculus L, Superior longitudinal fasciculus (temporal part) L
T1	Trail Making B	Corticospinal tract L, Cingulum (hippocampus) L, Forceps major, Superior longitudinal fasciculus R, Superior longitudinal fasciculus (temporal part) L, Superior longitudinal fasciculus (temporal part) R
DTI		
FA	Trail Making A	Anterior thalamic radiation L, Corticospinal tract R, Forceps major, Inferior longitudinal fasciculus L, Inferior longitudinal fasciculus R, Superior longitudinal fasciculus R
FA	Trail Making B	Anterior thalamic radiation L, Corticospinal tract R, Forceps major, Inferior longitudinal fasciculus R, Superior longitudinal fasciculus R, Superior longitudinal fasciculus (temporal part) R
AD	Trail Making A	Corticospinal tract R, Forceps major, Forceps minor, Superior longitudinal fasciculus L, Superior longitudinal fasciculus R, Superior longitudinal fasciculus (temporal part) L
AD	Trail Making B	Corticospinal tract R, Forceps minor, Superior longitudinal fasciculus L, Superior longitudinal fasciculus R, Uncinate fasciculus R, Superior longitudinal fasciculus (temporal part) L
MD	Trail Making A	Forceps major, Inferior fronto-occipital fasciculus R, Superior longitudinal fasciculus L, Superior longitudinal fasciculus R, Uncinate fasciculus L, Superior longitudinal fasciculus (temporal part) R
MD	Trail Making B	Corticospinal tract R, Forceps minor, Inferior fronto-occipital fasciculus R, Superior longitudinal fasciculus R, Uncinate fasciculus L, Uncinate fasciculus R
RD	Trail Making A	Cingulum (cingulate gyrus) L, Cingulum (hippocampus) R, Inferior fronto-occipital fasciculus R, Superior longitudinal fasciculus L, Superior longitudinal fasciculus R, Uncinate fasciculus L
RD	Trail Making B	Anterior thalamic radiation L, Cingulum (hippocampus) R, Superior longitudinal fasciculus R, Uncinate fasciculus L, Uncinate fasciculus R, Superior longitudinal fasciculus (temporal part) L
NODDI		
ODI	Trail Making A	Anterior thalamic radiation L, Cingulum (hippocampus) L, Cingulum (hippocampus) R, Inferior longitudinal fasciculus R, Uncinate fasciculus L, Superior longitudinal fasciculus (temporal part) R
ODI	Trail Making B	Corticospinal tract L, Cingulum (hippocampus) L, Cingulum (hippocampus) R, Inferior longitudinal fasciculus R, Superior longitudinal fasciculus R, Uncinate fasciculus L
Vic	Trail Making A	Cingulum (hippocampus) L, Inferior longitudinal fasciculus L, Superior longitudinal fasciculus R, Uncinate fasciculus L, Uncinate fasciculus R, Superior longitudinal fasciculus (temporal part) L
Vic	Trail Making B	Inferior longitudinal fasciculus L, Corticospinal tract L, Cingulum (hippocampus) L, Forceps major, Inferior longitudinal fasciculus R, Uncinate fasciculus R

Results

Trail-making task completion time (seconds) was used as an indicator of cognitive impairment.

Feature ranking using the DT method, identifying the top 33% of important features, improved mean accuracy by approximately 11.4%

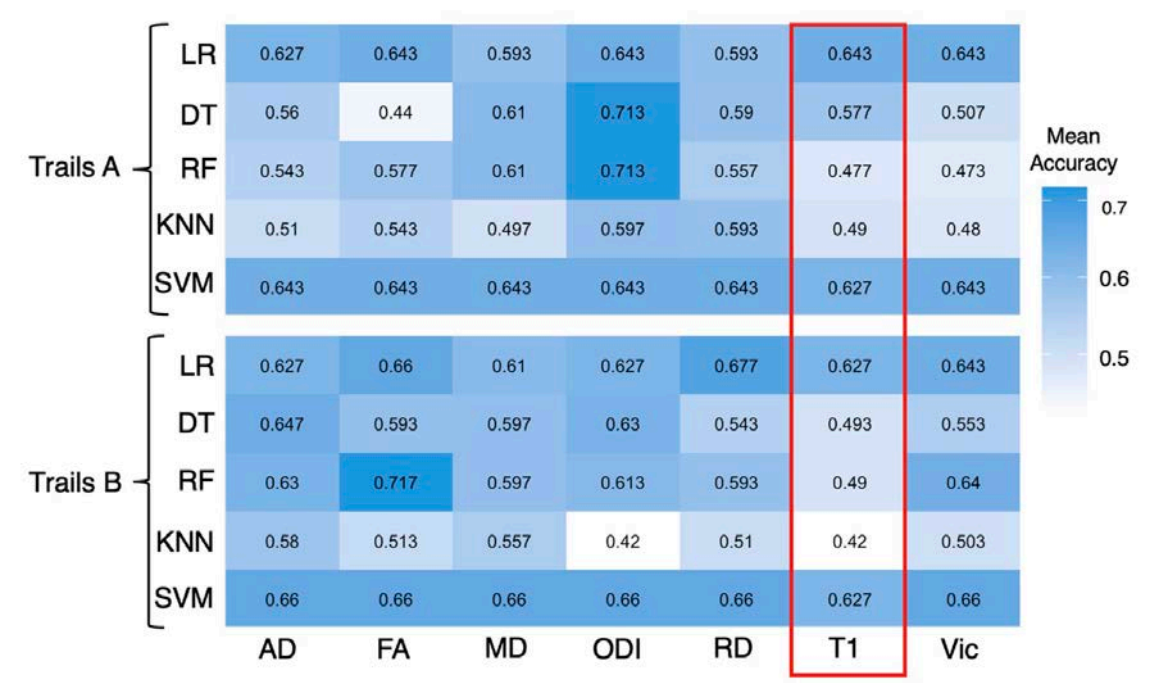
DTI models exhibited the higher accuracy, outperforming structural based model.



Results

Also trained other models including Linear regression, Decision tree, Random Forest, SVM, and averaged their accuracy for each biomarker for both tasks.

Results show that models trained using DTI and NODDI biomarkers outperform T1-based models significantly.

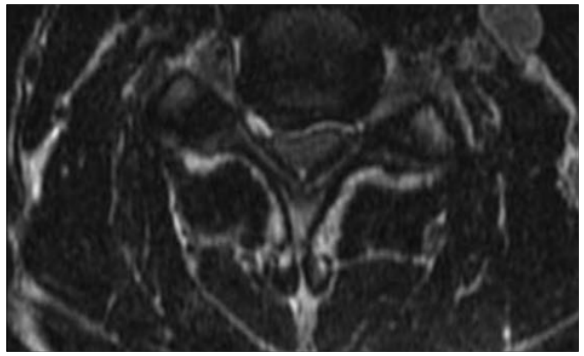


	Mean Accuracy	P-Value
T1	55.1%	-
FA	61.0%	0.030
AD	61.5%	0.009
MD	61.0%	0.005
RD	61.0%	0.004
Vic	59.0%	0.036
ODI	67.7%	0.001

Conclusion

- This study pioneered the use of ML-based classification algorithm using DTI and NODDI for the diagnosis of chronic traumatic brain injury (cTBI) within a real clinical setting.
- DTI and NODDI consistently outperformed T1-weighted imaging across various ML algorithms.
- Feature reduction techniques, particularly the DT method, significantly improved the performance of the K-NN model, suggesting localized effects of cTBI on specific brain regions.

Papers



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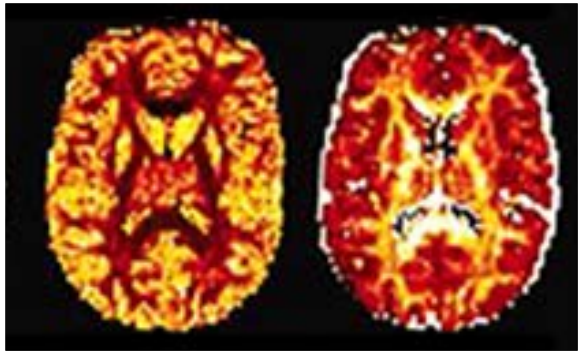
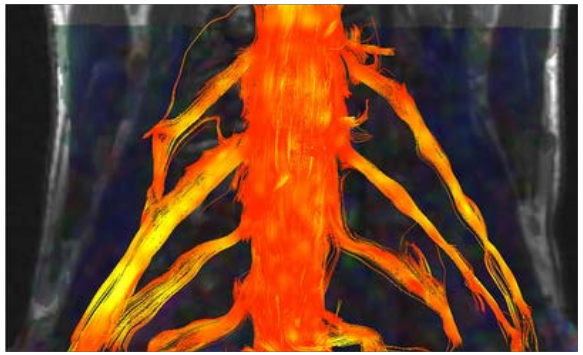
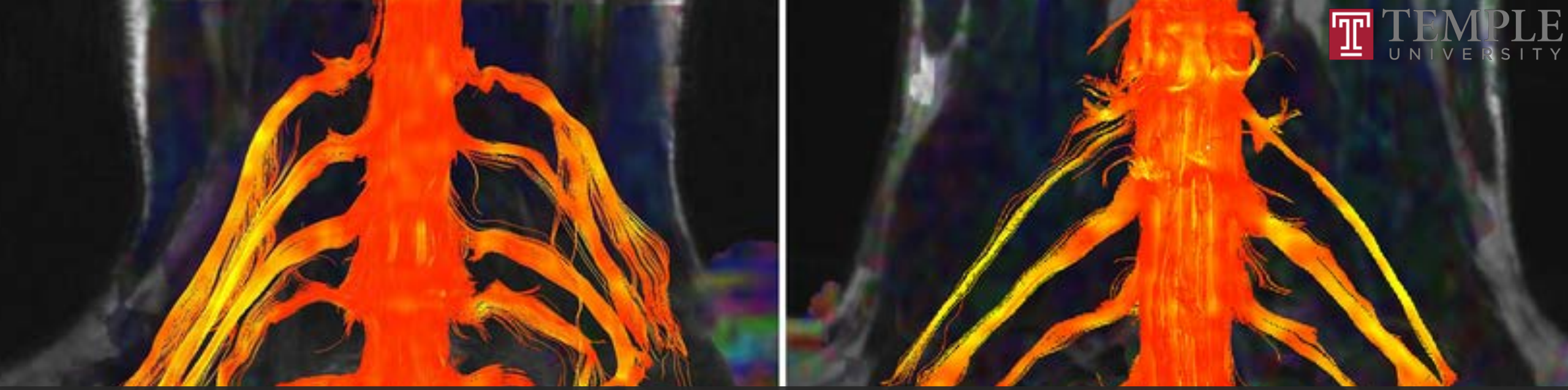




Paper 3

Quantitative Analysis in Cervical Spinal Cord Injury Patients Using Diffusion Tensor Imaging and Tractography



Paper 3

Quantitative Analysis in Cervical Spinal Cord Injury Patients Using Diffusion Tensor Imaging and Tractography

Objective

Investigate the clinical usefulness DTI and tractography in the prediction of outcomes after traumatic cervical spinal cord injury (SCI) and to assess whether the predictability is different before and after surgery.

Subjects

Sixty-one subjects with traumatic cervical SCI were randomly assigned to preop or postop groups and received DTI accordingly.

Data

DTI scan before and after surgery was performed for each subject based on their groups. Neurological status and functional status were assessed at 4 and 8 weeks after SCI.

Method

Using Statistical analysis to uncover the usefulness DTI outcomes prediction after SCI and the effect of the time of the scan on its ability for prediction.

Park, G. S., Kim, T. U., Lee, S. J., Hyun, J. K., & Kim, S. Y. (2022). Quantitative analysis in cervical spinal cord injury patients using diffusion tensor imaging and tractography. Annals of Rehabilitation Medicine, 46 (4), 172.

Spinal Cord Injury

A devastating condition resulting from trauma to the spinal cord, often leading to partial or complete loss of motor and sensory function

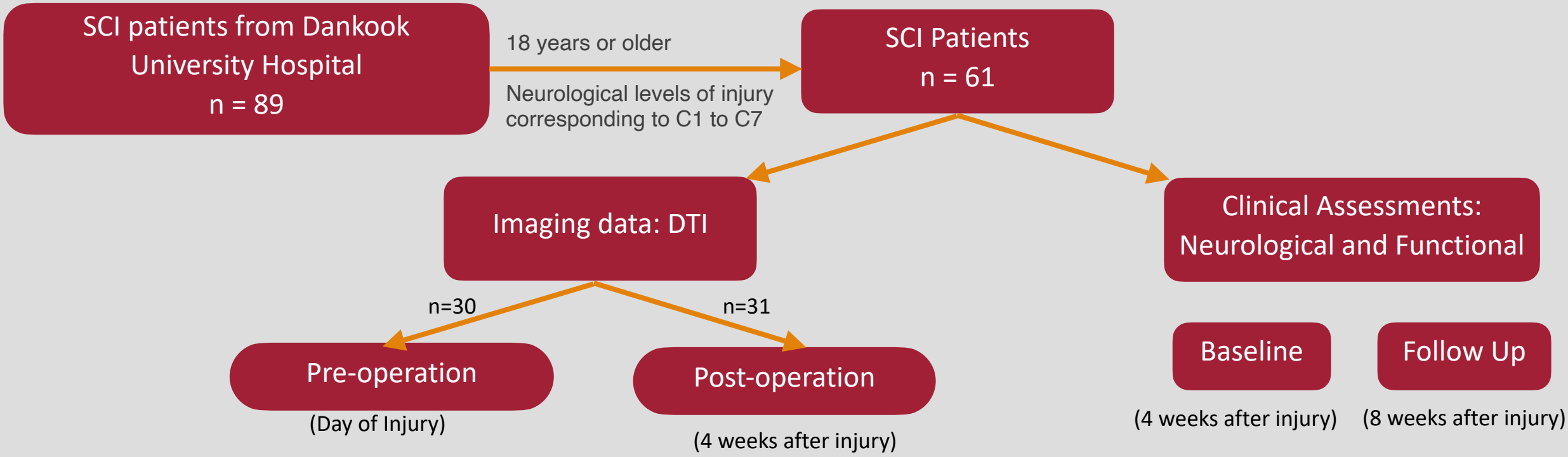
Predicting outcomes after SCI is crucial for treatment planning and rehabilitation, but conventional imaging methods often lack the sensitivity to assess subtle changes in the spinal cord.

DTI has been extensively used in the brain to predict outcomes in various neurological conditions, but its application in spinal cord injury is less explored.

Timing of imaging acquisition can significantly impact the predictability of DTI, particularly in the context of spinal cord injury where the pathological processes evolve rapidly, especially around the time of surgery.

Understanding the clinical utility of DTI and tractography, in addition to the best time for image acquisition for predicting outcomes after traumatic cervical SCI is essential for optimizing patient management and rehabilitation strategies.

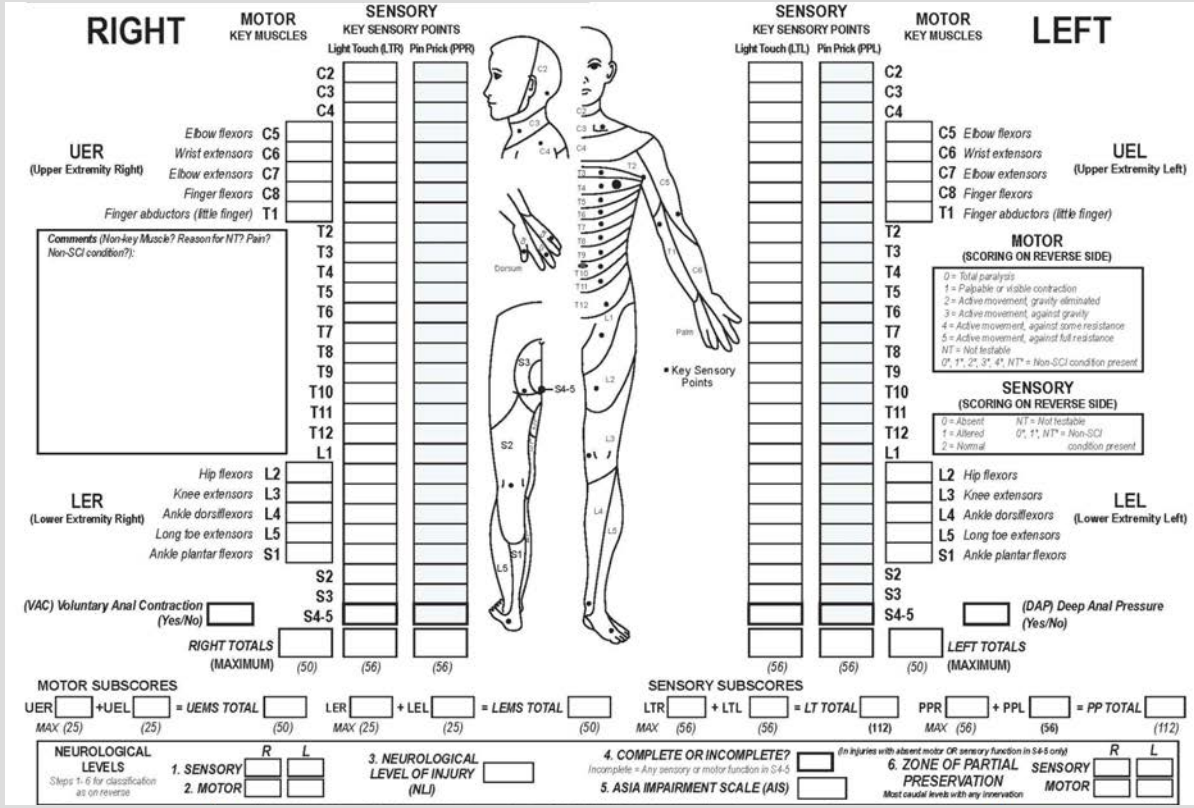
Subjects


SCI patients from Dankook University Hospital
n = 89
18 years or older
Neurological levels of injury corresponding to C1 to C7
SCI Patients
n = 61
Imaging data: DTI
Clinical Assessments: Neurological and Functional
n=30
n=31
Pre-operation
(Day of Injury)
Post-operation
(4 weeks after injury)
Baseline
(4 weeks after injury)
Follow Up
(8 weeks after injury)

Neurological Assessments

Utilized the International Standards for the Neurological Classification of Spinal Cord Injury (ISNCSCI), a protocol established by the American Spinal Injury Association (ASIA).

Evaluation parameters encompassed:
Upper and lower extremity motor function (0-50)
Light touch and pinprick sensory responses across upper and lower extremity dermatomes (0-112)



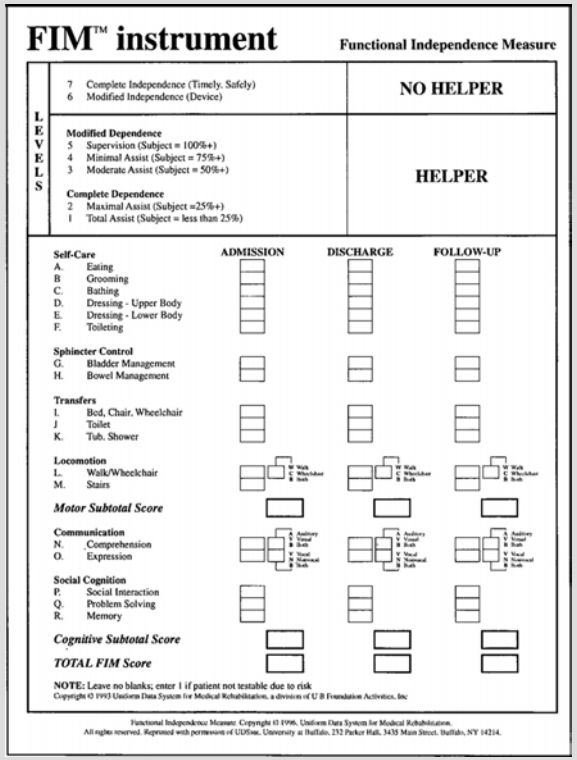
Functional Assessments

Utilized the Modified Barthel Index (MBI) and Functional Independence Measure (FIM) at baseline and follow-up evaluations.

MBI: Assess functional independence in activities of daily living, scored from 0 (completely dependent) to 100 (independent in basic ADLs).

FIM: Assessment tool in rehabilitation settings, comprising items across six areas graded based on independence levels from 1 (total assistance required) to 7 (complete independence).

For this study, total MBI score, total FIM score (FIM total) and motor scores (FIM motor: self-care, sphincter control, and transfer/locomotion) were utilized.

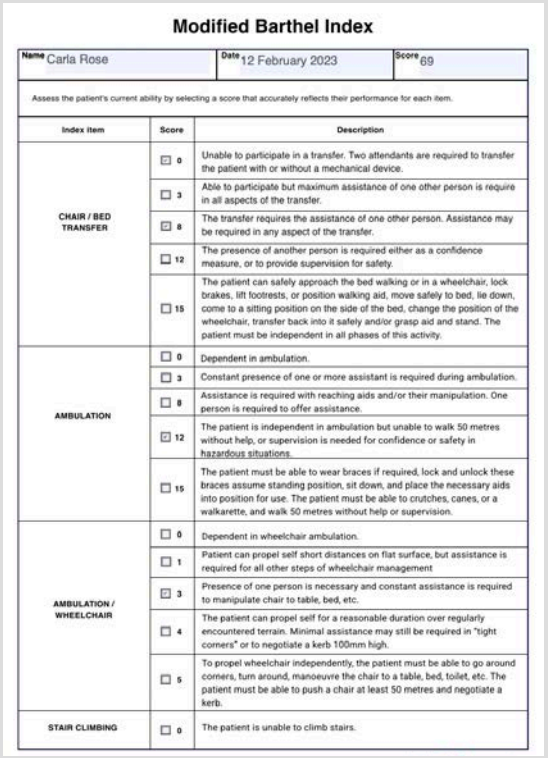


FIM™ instrument — Functional Independence Measure

LEVELS	
7 Complete Independence (Timely, Safely) 6 Modified Independence (Device)	NO HELPER
Modified Dependence 5 Supervision (Subject = 100%+) 4 Minimal Assist (Subject = 75%+) 3 Moderate Assist (Subject = 50%+) **Complete Dependence** 2 Maximal Assist (Subject =25%+) 1 Total Assist (Subject = less than 25%)	HELPER

	ADMISSION	DISCHARGE	FOLLOW-UP
Self-Care			
A. Eating			
B Grooming			
C. Bathing			
D. Dressing - Upper Body			
E. Dressing - Lower Body			
F. Toileting			
Sphincter Control			
G. Bladder Management			
H. Bowel Management			
Transfers			
I. Bed, Chair, Wheelchair			
J Toilet			
K. Tub, Shower			
Locomotion			
L. Walk/Wheelchair			
M. Stairs			
Motor Subtotal Score			
Communication			
N. Comprehension			
O. Expression			
Social Cognition			
P. Social Interaction			
Q. Problem Solving			
R. Memory			
Cognitive Subtotal Score			
TOTAL FIM Score			

NOTE: Leave no blanks; enter 1 if patient not testable due to risk



Modified Barthel Index

Name: Carla Rose | Date: 12 February 2023 | Score: 69

Assess the patient's current ability by selecting a score that accurately reflects their performance for each item.

Index item	Score	Description
CHAIR / BED TRANSFER	☑ 0	Unable to participate in a transfer. Two attendants are required to transfer the patient with or without a mechanical device.
	☐ 3	Able to participate but maximum assistance of one other person is require in all aspects of the transfer.
	☑ 8	The transfer requires the assistance of one other person. Assistance may be required in any aspect of the transfer.
	☐ 12	The presence of another person is required either as a confidence measure, or to provide supervision for safety.
	☐ 15	The patient can safely approach the bed walking or in a wheelchair, lock brakes, lift footrests, or position walking aid, move safely to bed, lie down, come to a sitting position on the side of the bed, change the position of the wheelchair, transfer back into it safely and/or grasp aid and stand. The patient must be independent in all phases of this activity.
AMBULATION	☐ 0	Dependent in ambulation.
	☐ 3	Constant presence of one or more assistant is required during ambulation.
	☐ 8	Assistance is required with reaching aids and/or their manipulation. One person is required to offer assistance.
	☑ 12	The patient is independent in ambulation but unable to walk 50 metres without help, or supervision is needed for confidence or safety in hazardous situations.
	☐ 15	The patient must be able to wear braces if required, lock and unlock these braces assume standing position, sit down, and place the necessary aids into position for use. The patient must be able to crutches, canes, or a walkarette, and walk 50 metres without help or supervision.
AMBULATION / WHEELCHAIR	☐ 0	Dependent in wheelchair ambulation.
	☐ 1	Patient can propel self short distances on flat surface, but assistance is required for all other steps of wheelchair management
	☑ 3	Presence of one person is necessary and constant assistance is required to manipulate chair to table, bed, etc.
	☐ 4	The patient can propel self for a reasonable duration over regularly encountered terrain. Minimal assistance may still be required in "tight corners" or to negotiate a kerb 100mm high.
	☐ 5	To propel wheelchair independently, the patient must be able to go around corners, turn around, manoeuvre the chair to a table, bed, toilet, etc. The patient must be able to push a chair at least 50 metres and negotiate a kerb.
STAIR CLIMBING	☐ 0	The patient is unable to climb stairs.

Clinical Assessments

For each subject in preop and post groups the baseline and followup clinical assessments was performed.

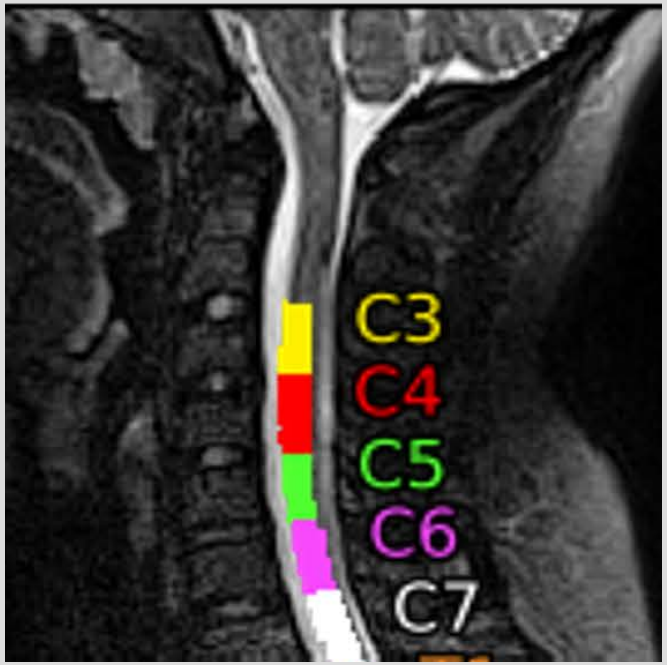
	Features	Range	Baselin	Followup
Neurological Scores	Upper extremity motor	0-56		
	Upper extremity Sensory (Light touch)	0-112		
	Upper extremity Sensory (Pinprick)	0-112		
	Upper extremity Sensory (Total)	0-112		
	Lower extremity motor	0-56		
	Lower extremity Sensory (Light touch)	0-112		
	Lower extremity Sensory (Pinprick)	0-112		
	Lower extremity Sensory (Total)	0-112		
Functional Scores	MBI	0-100		
	FIM(Self-care)	0-42		
	FIM(Sphincter control)	0-14		
	FIM(Transfer/locomotion)	0-35		
	FIM(total)	0-91		

Data Preprocessing

DTI metrics, including FA, MD, and fibers tracts were computed from DTI images.

Biomarkers were localized to different levels of the spine, from C3 to C7, including the level of injury, to assess regional variations in microstructural alterations.

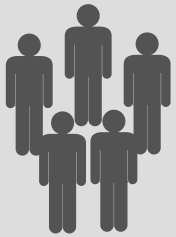
	FA	MD	Number of Fibers	Crossing Fibers from C3 to
C3				-
C4				
C5				
C6				
C7				
Level of injury				



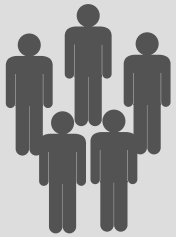
Analysis

DTI biomarkers and clinical scores was analyzed using to explore functional and neurological changes, impact of surgery on DTI parameters, and correlations between DTI metrics and assessment scores in both groups, all performed using the Mann-Whitney U test for comparison between two groups.

Preop



Postop



DTI Biomarkers

	FA	M	Number of	Crossing Fibers from C3
C3				-
C4				
C5				
C6				
C7				
Level of				

Clinical Scores

	Features	Baseline	Followup
Neurological Scores	Upper extremity motor		
	Upper extremity Sensory (Light touch)		
	Upper extremity Sensory (Pinprick)		
	Upper extremity Sensory (Total)		
	Lower extremity motor		
	Lower extremity Sensory (Light touch)		
	Lower extremity Sensory (Pinprick)		
	Lower extremity Sensory (Total)		
Functional Scores	MBI		
	FIM(Self-care)		
	FIM(Sphincter control)		
	FIM(Transfer/locomotion)		
	FIM(total)		

Analysis: Neurologic and Functional Changes from Baseline to Followup

Comparison of baseline and follow-up evaluations to assess functional and neurological changes over time.

Evaluation of differences between the two groups.

Both groups Showed Significant Improvements in UEM, MBI, and all FIM subscales from baseline to Followup.

No significant differences between preop and postop in improvements except for pinprick.

Neurologic and functional changes between the preop and postop groups

	Preop group (n=24)			Postop group (n=14)			p-value[b] (preop vs. postop)	
	Baseline	Follow-up	p-value[a]	Baseline	Follow-up	p-value[a]	Baseline	Follow-up
Upper extremity								
Motor	29.25±13.53	36.78±13.44	0.000*	31.29±12.29	39.57±9.14	0.001*	0.422	0.851
Sensory								
Light touch	14.04±3.98	15.87±4.33	0.012*	12.79±4.34	14.43±4.60	0.068	0.220	0.301
Pinprick	15.58±4.38	16.78±4.38	0.100	12.86±4.29	14.43±4.60	0.109	0.045*	0.118
Total	29.63±7.82	32.65±8.20	0.012*	25.64±8.63	28.86±9.21	0.144	0.104	0.314
Lower extremity								
Motor	39.88±17.19	40.52±17.41	0.440	44.00±10.55	48.21±3.73	0.068	0.363	0.321
Sensory								
Light touch	16.96±4.39	16.87±5.29	0.888	14.64±4.99	14.64±4.99	1.000	0.168	0.145
Pinprick	17.21±4.13	16.78±5.55	0.750	14.64±4.99	14.64±4.99	1.000	0.128	0.145
Total	34.17±8.30	33.65±10.77	0.888	29.29±9.97	29.29±9.97	1.000	0.161	0.185
K-MBI	30.13±28.82	53.41±34.76	0.000*	47.36±38.23	71.44±31.28	0.028*	0.113	0.184
FIM								
Self-care	12.46±7.18	18.73±12.11	0.001*	18.64±13.77	28.67±14.97	0.042*	0.314	0.052
Sphincter control	8.88±5.09	11.27±4.59	0.008*	9.64±4.80	12.44±3.13	0.039*	0.705	0.532
Transfer/locomotion	10.71±7.17	17.91±11.23	0.001*	17.86±12.37	23.78±12.12	0.042*	0.123	0.203
Total	65.58±19.99	82.23±27.60	0.000*	81.36±29.10	98.56±30.35	0.043*	0.130	0.191

Analysis: Effect of surgery on DTI Biomarkers

Examination of DTI parameters for both preoperative and postoperative groups to assess the impact of surgery on DTI metrics and failure rates.

DTI parameters between the preop and postop groups

	Preop group (n=24)	Postop group (n=14)	p-value
FA			
C3	0.772±0.078	0.606±0.112	0.000*
C4	0.700±0.102	0.568±0.136	0.006*
C5	0.664±0.102	0.612±0.120	0.066
C6	0.609±0.134	0.604±0.153	0.873
C7	0.676±0.125	0.573±0.173	0.085
Cinj	0.621±0.110	0.607±0.171	0.575
MD			
C3	0.845±0.133	1.165±0.396	0.001*
C4	0.877±0.179	1.202±0.394	0.003*
C5	0.893±0.184	1.133±0.381	0.016*
C6	0.926±0.251	1.084±0.347	0.060
C7	0.777±0.346	1.134±0.372	0.009*
Cinj	0.902±.0241	1.178±0.432	0.015*
Fiber No.			
C3	1245.78±279.24	874.36±415.10	0.009*
C4	1267.48±294.06	736.36±477.08	0.001*
C5	1262.09±313.31	618.57±440.89	0.000*
C6	1157.04±293.19	432.79±373.51	0.000*
C7	813.65±430.23	288.71±299.86	0.000*
Crossing fiber No.			
C3-5	348.48±300.92	259.43±275.32	0.363
C3-6	235.70±275.26	143.93±236.59	0.137
C3-7	49.61±128.45	63.64±155.04	0.484

Failure rate (due to metal interference) was significantly higher in the postop group (41.5%) than in the preop group (20%).

Significant Differences Observed between Preop and Postop groups in terms of quantitative DTI biomarkers

1) DTI and tractographic findings before surgery showed a lower failure rate for interpretation than those taken after surgery.

Analysis: Correlations between DTI parameters and baseline/follow-up evaluations (1)

Determination of which correlations are more significant for potential outcome predictions.

Correlation analysis between follow-up clinical findings and DTI parameters in the **preop** group

	FA					MD					Fiber No.					Crossing fiber No.		
	C3	C4	C5	C6	C7	C3	C4	C5	C6	C7	C3	C4	C5	C6	C7	C3-5	C3-6	C3-7
UE_FU																		
Motor	-0.021	0.079	-0.138	0.021	-0.172	0.004	0.075	0.207	0.011	0.338	0.296	0.101	0.219	0.042	0.387	0.221	0.130	0.165
Sensory																		
Light touch	0.161	0.571*	0.181	-0.142	-0.248	-0.142	-0.622*	-0.071	0.055	0.406	0.082	0.071	0.121	0.170	0.334	0.089	0.007	0.091
Pinprick	0.073	0.213	-0.003	-0.285	0.046	-0.121	-0.355	0.051	0.086	0.038	0.394	0.317	0.216	0.211	0.375	0.201	0.007	0.041
Total	0.084	0.466	0.206	-0.118	-0.108	-0.198	-0.561*	0.051	0.006	0.025	0.191	0.148	0.127	0.125	0.345	0.071	-0.060	0.-007
LE_FU																		
Motor	-0.044	0.019	-0.258	-0.224	-0.441	0.192	0.207	0.504*	0.284	0.582*	0.124	0.143	0.116	-0.056	0.168	0.004	0.007	0.016
Sensory																		
Light touch	0.113	-0.035	0.019	-0.146	-0.171	0.020	0.061	0.362	0.228	0.317	0.254	0.212	0.196	0.126	0.226	0.038	-0.027	-0.135
Pinprick	0.078	0.017	0.106	0.045	-0.101	-0.101	-0.026	0.205	-0.014	0.213	0.364	0.378	0.257	0.077	0.288	0.072	-0.064	-0.135
Total	0.095	-0.032	-0.007	-0.075	-0.170	-0.018	0.007	0.324	0.105	0.025	0.364	0.319	0.215	0.097	0.200	0.004	-0.010	-0.072
K-MBI_FU	0.280	0.128	0.149	0.060	0.035	-0.255	0.161	0.215	0.007	0.156	0.333	0.353	0.358	0.420	0.457*	0.233	0.211	0.152
FIM_FU																		
Self-care	0.190	0.053	0.142	0.126	0.089	-0.193	0.262	0.157	0.012	0.101	0.323	0.299	0.361	0.480*	0.461*	0.317	0.325	0.312
Sphincter control	0.002	0.037	0.081	-0.117	0.039	0.030	0.233	0.247	0.262	0.249	0.083	0.188	0.167	0.146	0.256	0.080	-0.048	-0.076
Transfer	0.228	-0.006	-0.111	-0.210	0.048	-0.210	0.219	0.381	0.165	0.099	0.312	0.359	0.307	0.308	0.381	0.115	0.084	0.041
Total	0.331	0.106	0.110	-0.040	0.078	-0.278	0.172	0.275	0.065	0.093	0.310	0.342	0.329	0.454*	0.482*	0.195	0.213	0.186

Baseline: No significant correlation!

Followup: Significant Correlation at some levels.

Analysis: Correlations between DTI parameters and baseline/follow-up evaluations (2)

Determination of which correlations are more significant for potential outcome predictions.

Baseline: Many significant correlation specially with baseline functional scores!

Followup: Significant Correlation at **some** levels.

2) Postoperative DTI parameters better reflected clinical states.

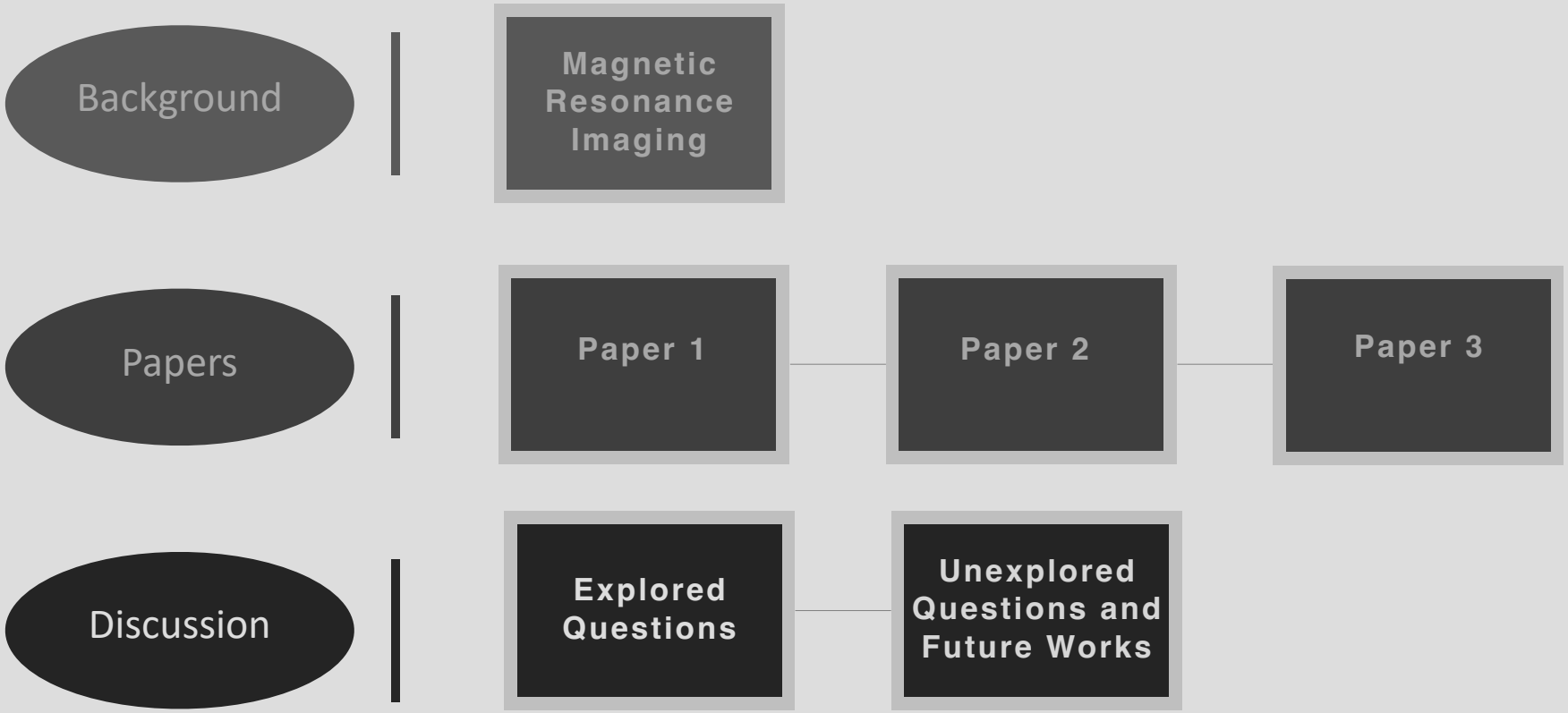
Correlation analysis between follow-up clinical findings and DTI parameters in the **postop** group

	FA					MD					Fiber No.					Crossing fiber No.		
	C3	C4	C5	C6	C7	C3	C4	C5	C6	C7	C3	C4	C5	C6	C7	C3-5	C3-6	C3-7
UE																		
Motor	0.736*	0.138	0.331	0.284	0.204	-0.366	0.325	0.096	0.185	-0.143	0.150	0.148	0.355	0.273	0.152	0.239	0.314	0.341
Sensory																		
Light touch	0.035	-0.334	-0.366	-0.174	0.016	-0.211	0.407	0.344	0.265	-0.006	0.095	0.116	0.198	0.044	0.054	0.142	0.059	0.123
Pinprick	-0.006	-0.391	-0.469	-0.253	-0.012	-0.126	0.295	0.228	0.156	0.000	-0.027	-0.027	0.059	-0.095	0.024	0.020	-0.032	0.071
Total	-0.006	-0.391	-0.469	-0.253	-0.012	-0.126	0.295	0.228	0.156	0.000	-0.027	-0.027	0.059	-0.095	0.024	0.020	-0.032	0.071
LE																		
Motor	0.007	-0.074	0.104	-0.026	-0.163	0.264	0.617*	0.576*	0.535	0.171	0.548*	0.496	0.690*	0.619*	-0.372	0.534*	0.491	0.396
Sensory																		
Light touch	-0.342	0.064	-0.150	0.257	0.321	0.150	-0.214	0.000	-0.235	-0.150	0.504	0.339	0.305	0.192	0.287	0.380	0.358	0.271
Pinprick	-0.342	0.064	-0.150	0.257	0.321	0.150	-0.214	0.000	-0.235	-0.150	0.504	0.339	0.305	0.192	0.287	0.380	0.358	0.271
Total	-0.342	0.064	-0.150	0.257	0.321	0.150	-0.214	0.000	-0.235	-0.150	0.504	0.339	0.305	0.192	0.287	0.380	0.358	0.271
K-MBI	0.366	0.149	0.292	0.022	-0.333	-0.033	0.311	0.096	0.245	0.426	0.460	0.535*	0.690*	0.563*	-0.099	0.599*	0.539*	0.522
FIM																		
Self-care	0.579*	0.096	0.202	0.094	-0.161	-0.348	0.305	0.136	0.296	0.283	0.246	0.336	0.434	0.442	0.232	0.444	0.419	0.550*
Sphincter control	0.150	0.252	0.402	0.122	-0.287	0.113	0.153	0.023	0.107	0.408	0.621*	0.694*	0.804*	0.632*	-0.119	0.676*	0.628*	0.501
Transfer	0.348	0.084	0.262	-0.042	-0.435	-0.095	0.318	0.117	0.295	0.510	0.413	0.528	0.662*	0.566*	-0.123	0.576*	0.516	0.577*
Total	0.338	0.132	0.264	-0.006	-0.360	-0.105	0.261	0.085	0.261	0.476	0.451	0.570*	0.697*	0.607	-0.011	0.608*	0.548*	0.564

Conclusion

- Notable differences were observed in DTI parameters before and after surgery.
- Preoperative DTI and tractography demonstrated lower interpretation failure rates than those obtained after surgery.
- Postoperative data significantly reflected the patient's clinical state at the time of evaluation.
- DTI and tractography could be useful in predicting clinical outcomes after traumatic cervical SCI and should be interpreted separately before and after spine surgery.

Outline


Background
Magnetic Resonance Imaging
Papers
Paper 1
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Paper 3
Discussion
Explored Questions
Unexplored Questions and Future Works

Explored Questions

- MRI integration with quantitative analysis and ML methods advances neurological disorder detection.
- Structural and DTI MRI Images can be used to train ML models achieve high accuracy in classifying neurological disorders, and predict functional outcomes.
- Preoperative DTI exhibits lower failing rate, while postoperative data better reflects clinical status and can be used for outcome prediction for spinal cord related abnormalities.

Unexplored Questions and Future Works

Structural images have demonstrated high accuracy in classifying spinal cord disorders, while DTI has shown superior information over structural imaging in brain studies. Additionally, predictive capabilities of DTI in various neurological conditions.

- Future research can involve training DTI-based models for spinal cord disorders classification.
- ML techniques can be employed for outcome prediction, particularly in spinal cord disorders.
- Exploring multimodal approaches, such as combining structural imaging and DTI, could enhance diagnostic accuracy and outcome prediction in neurological disorders.

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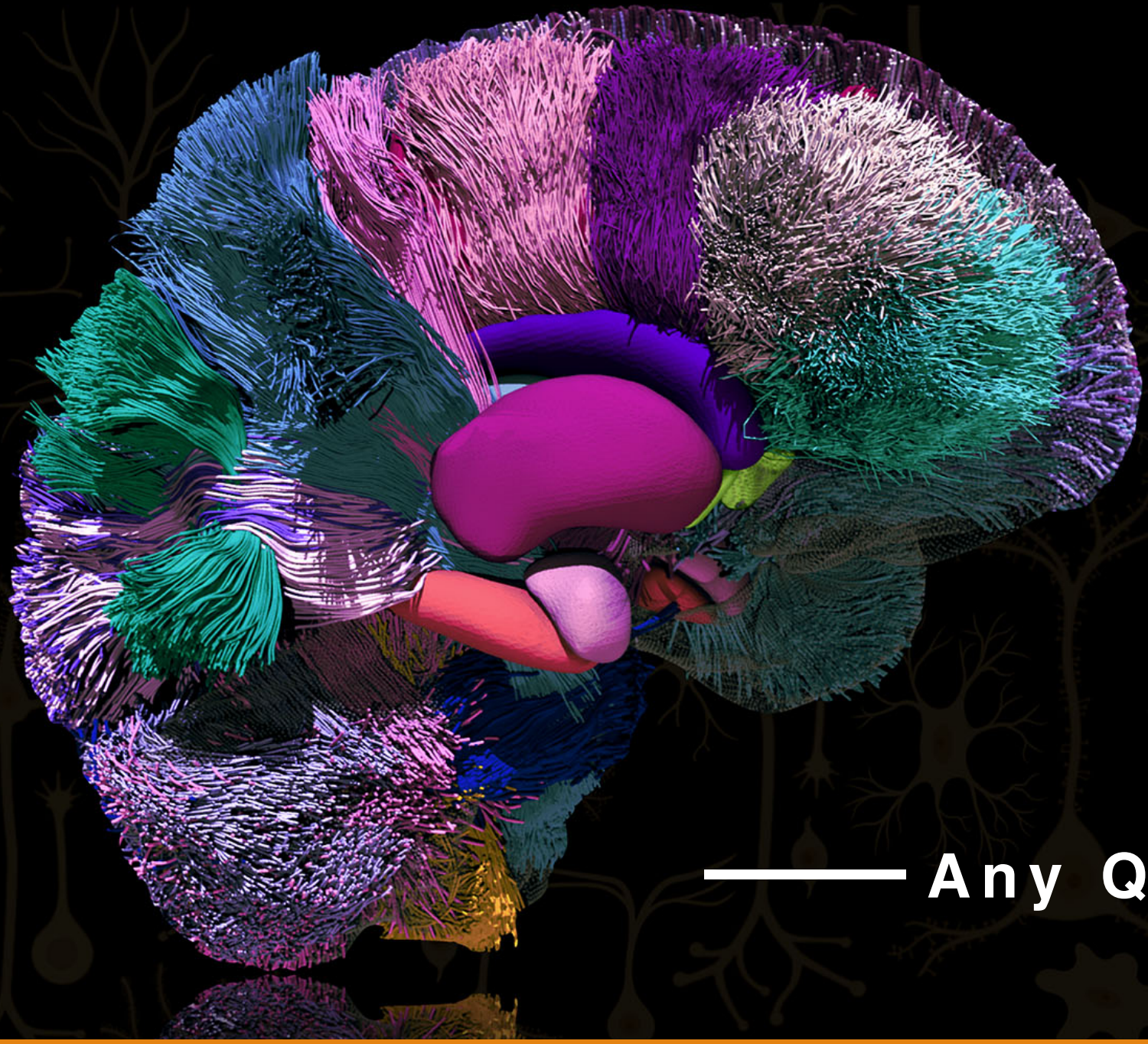

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Any Questions?