Applying Machine Learning to Identify Functional Classifiers in the Kidney From Resting-State MRI Spectra

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Project Goals

- Autonomously identify functional classifiers that distinguish pathology from healthy kidney
  - Use spectra from repeated “resting state” MRI of the kidney

- THIS STAGE : Get machine learning to recognize kidney cortex vs. medulla

- END GOAL : Identify functional classifiers that detect kidney disease and response to therapies

Overview

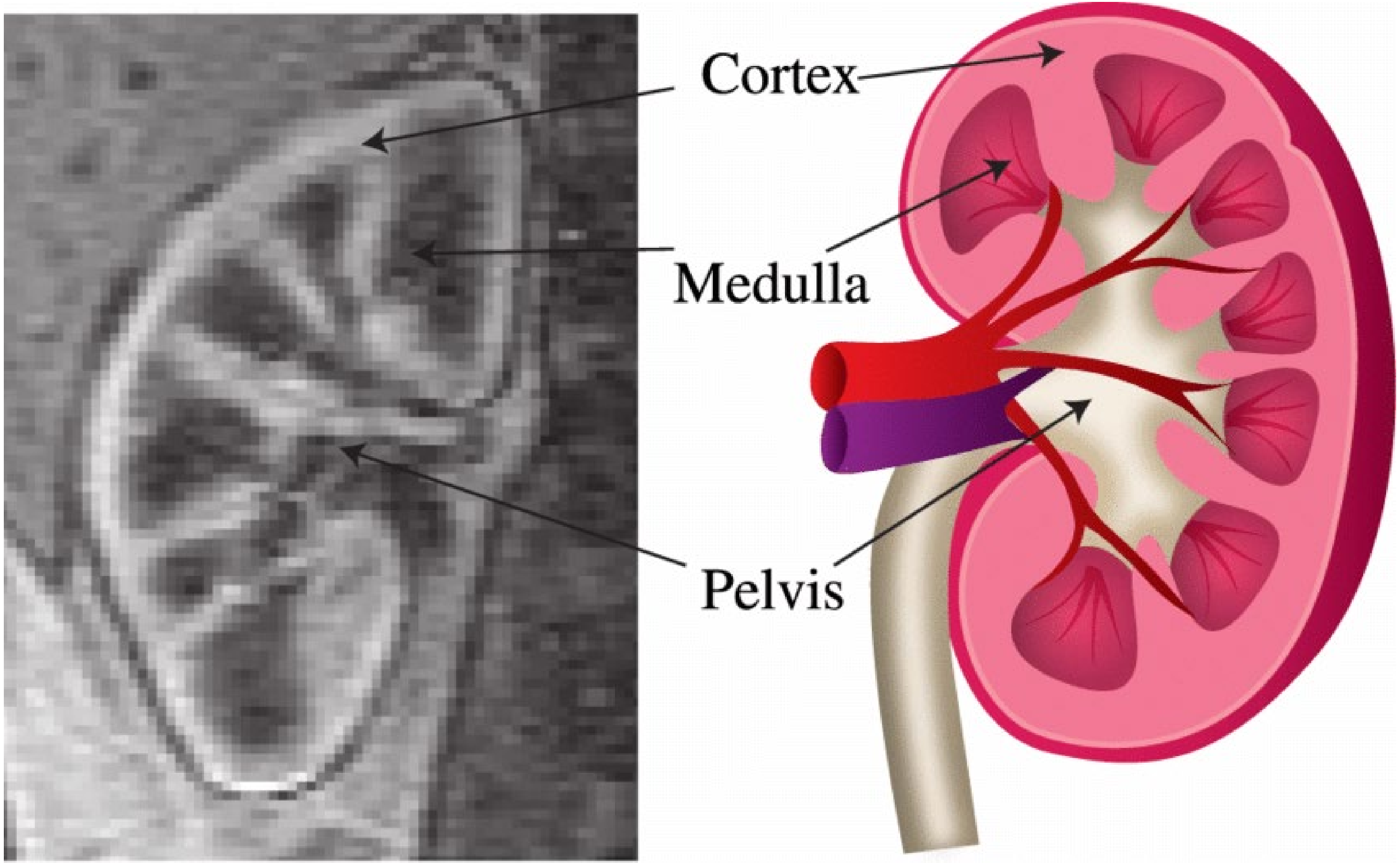
- Repeated MRI scanning reveals physiological fluctuations associated with specific tissues

- This is the basis for “resting state” functional MRI

- Spectral features of these time series in each voxel can be linked to physiological autoregulation, critical to kidney health

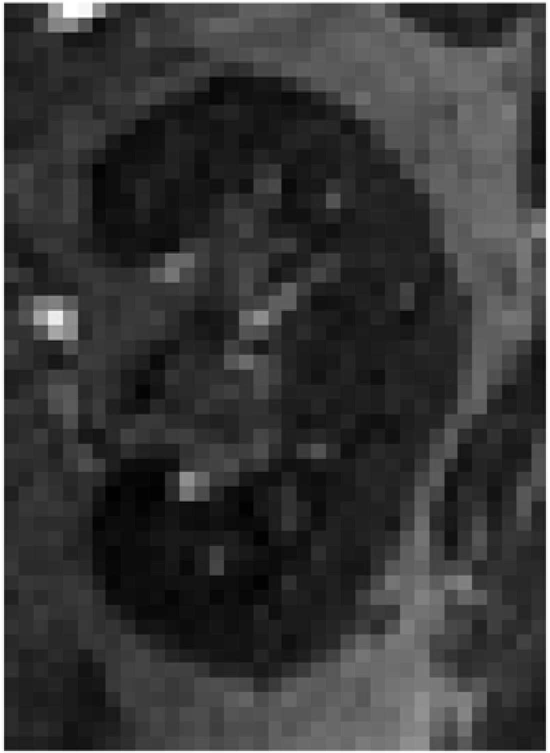
- Applied Random Forest machine learning model

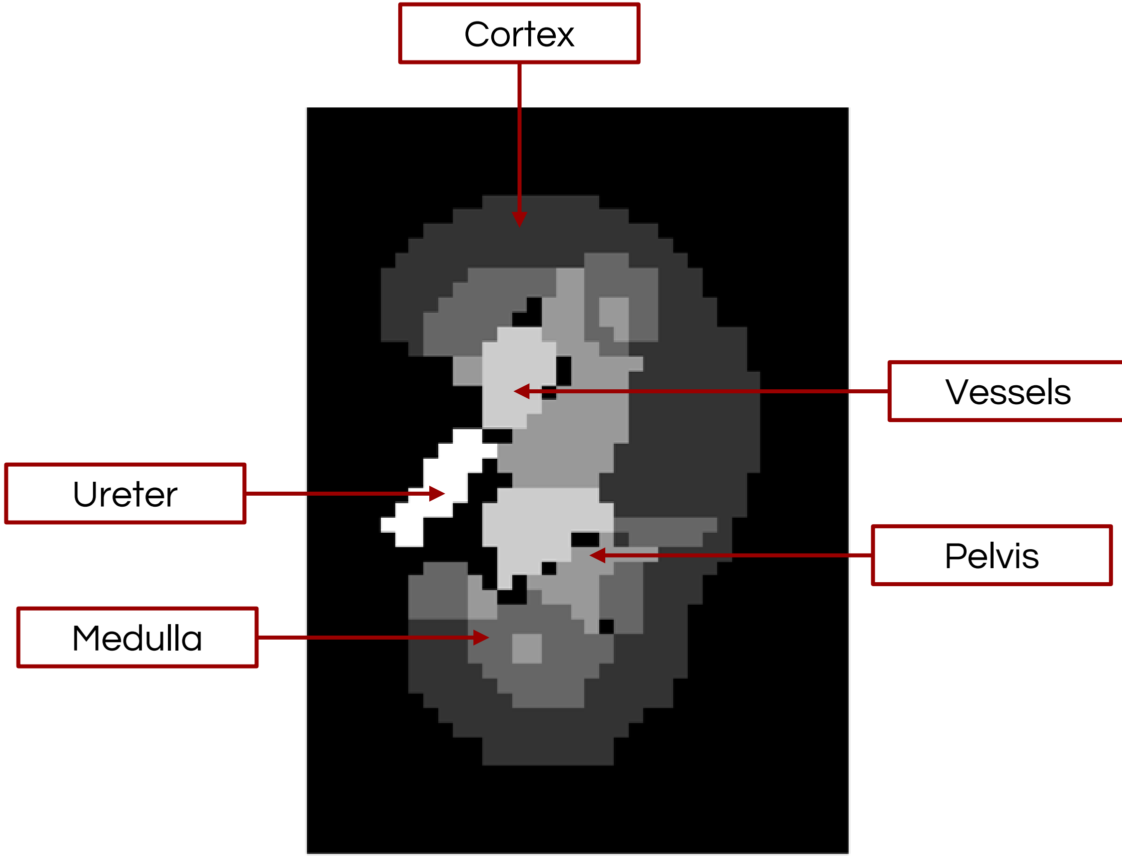
- Successfully trained and generated a prediction of features in a human kidney



Hodneland, et al. *Introduction*. 2014

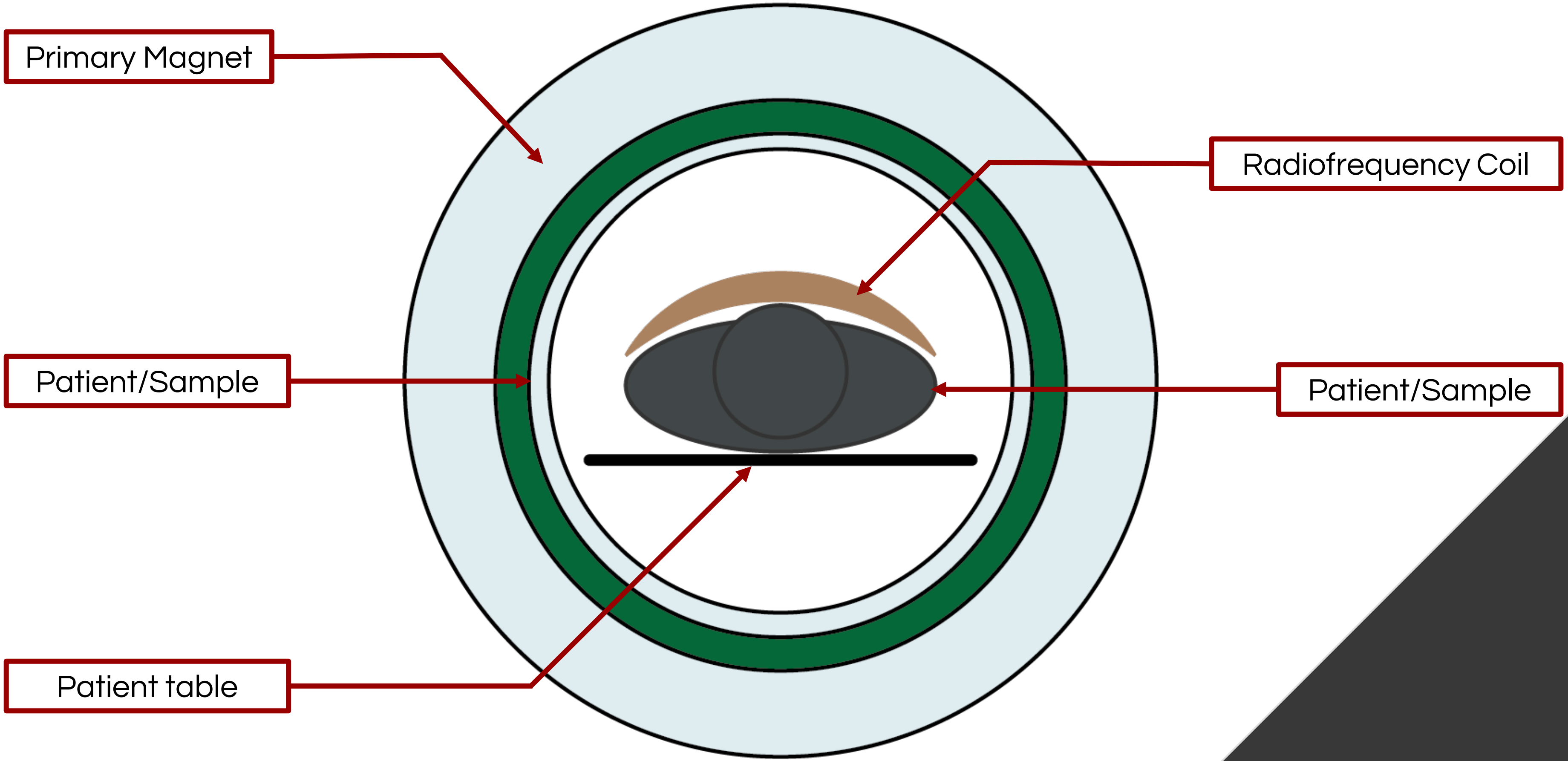
Image Coronal





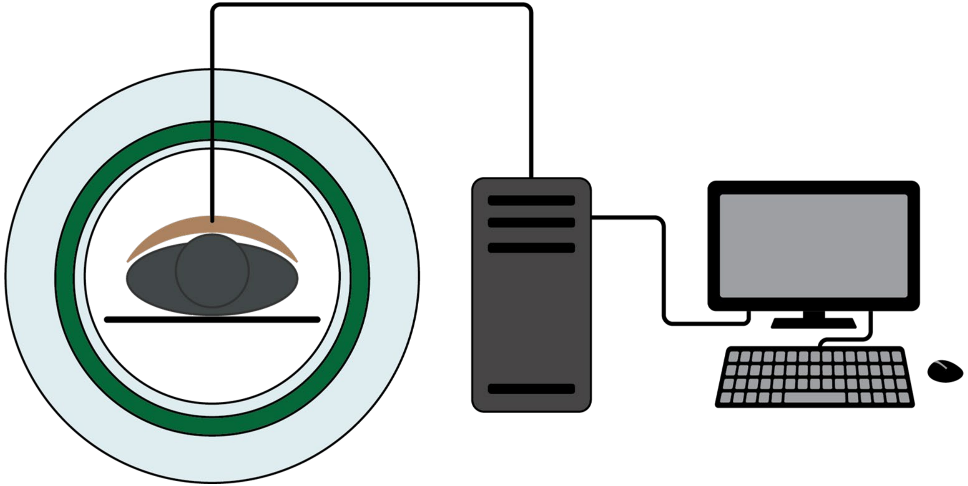
How is Data collected Using Magnetic Resonance?

MRI Fundamentals

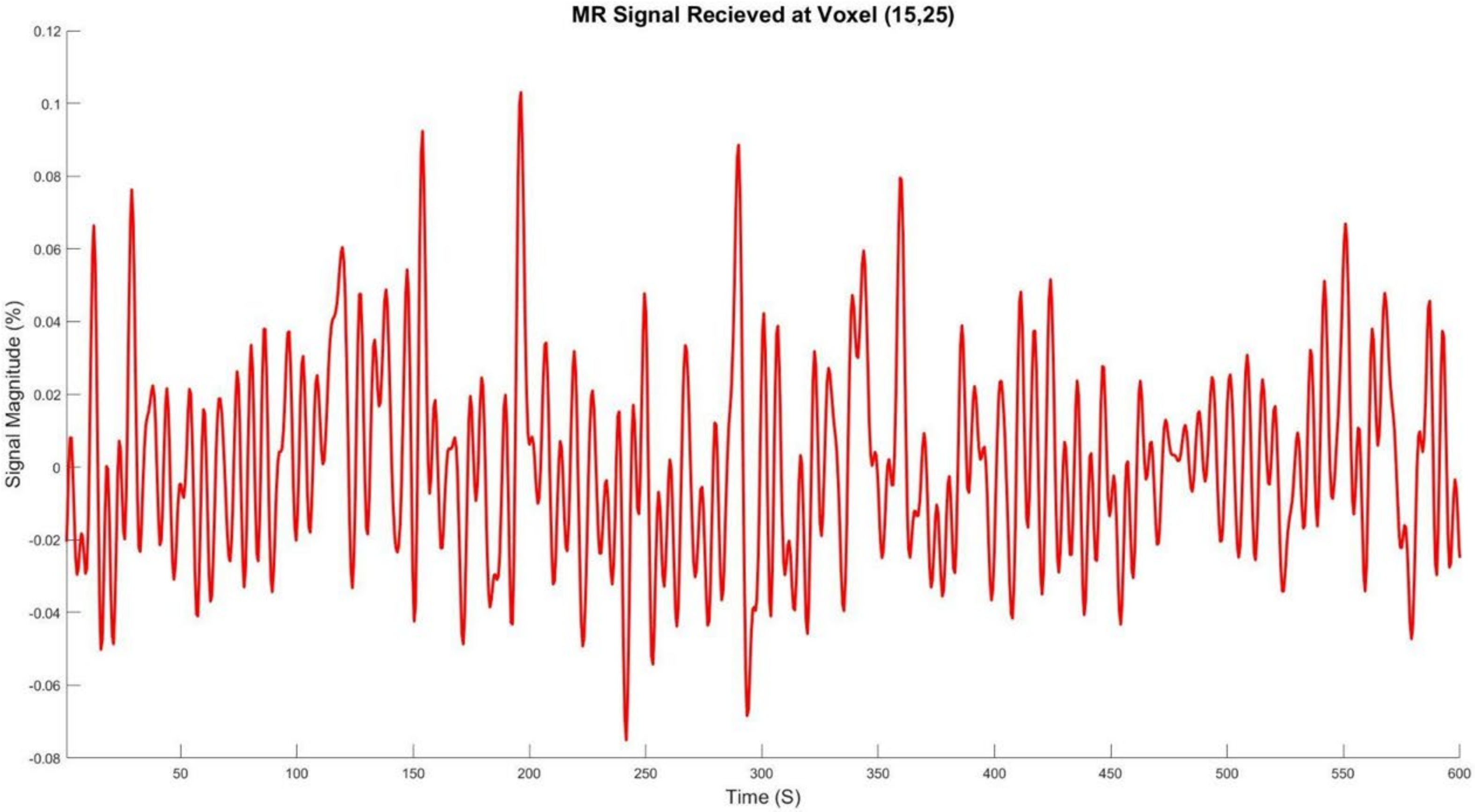


Detecting Signal

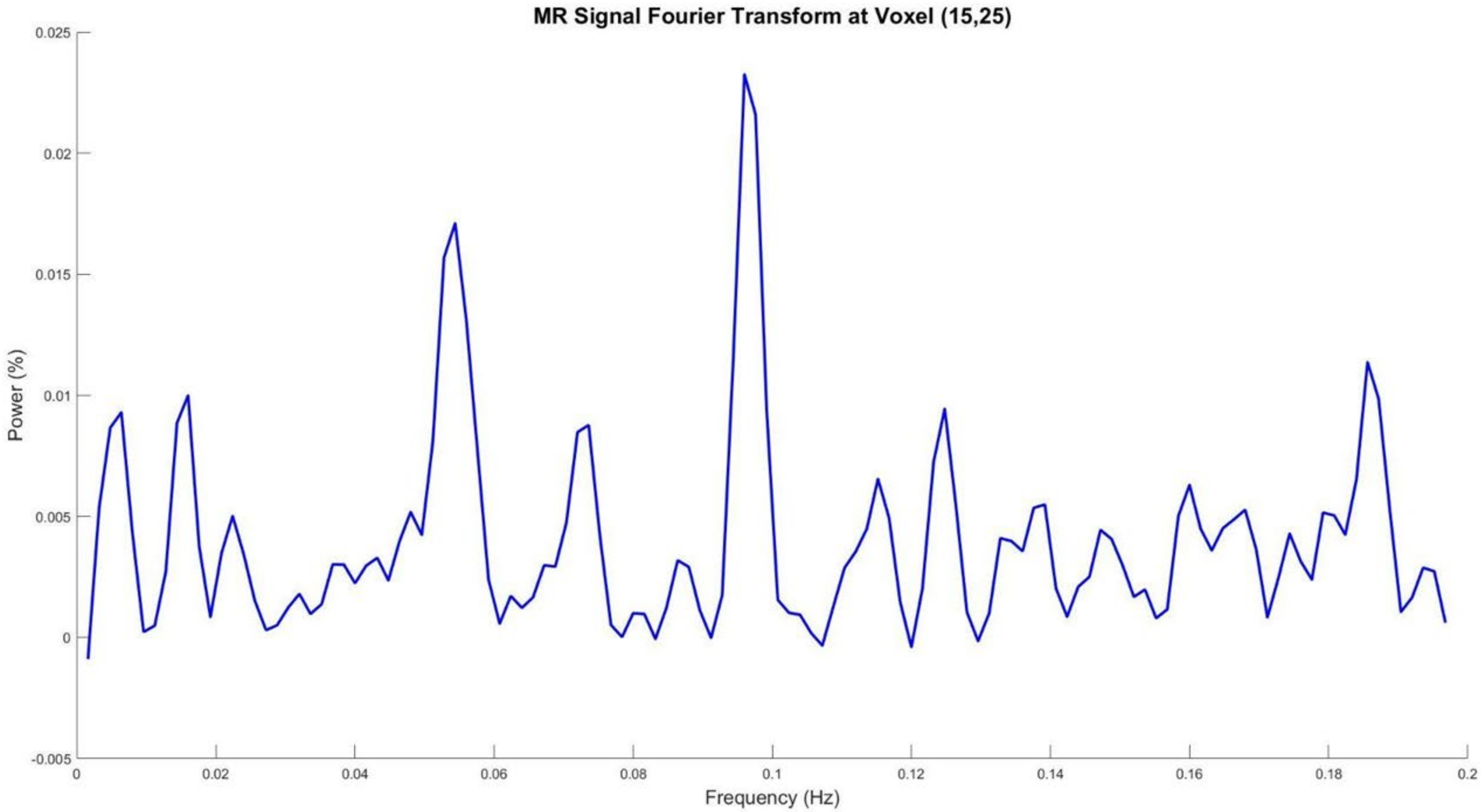
- Primary magnet distorts hydrogen atoms in the body
- Gradient coils isolates magnetic field to a desired point
- RF coil detects signal
- Signal is recorded in onboard computer



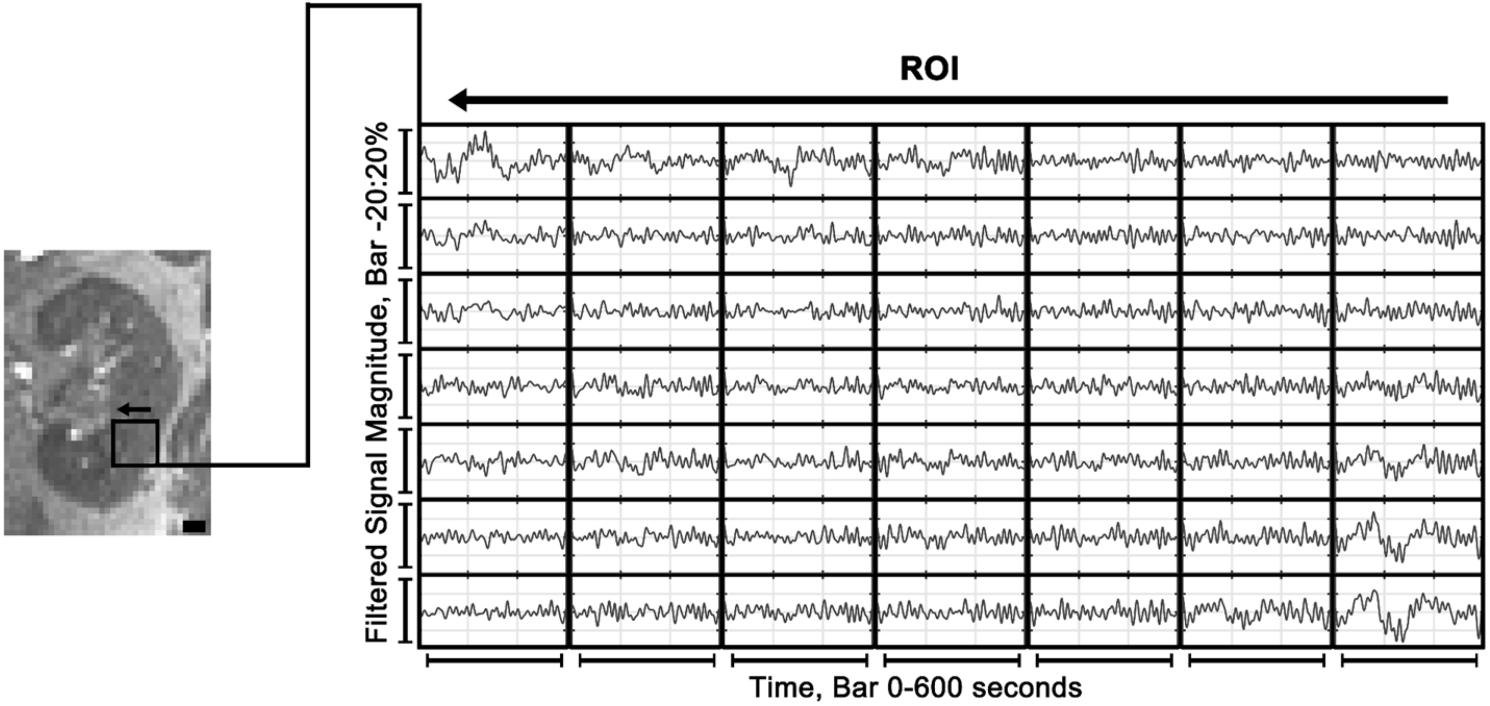
MRI time series in a single voxel, showing spontaneous fluctuations in the MRI signal that reflect underlying natural physiological processes, including autoregulation of perfusion.



Spectral features of the resting state time series in each voxel confirm the likely association of the fluctuations With known frequencies associated with physiological processes.



The time series vary spatially, demonstrating that they are physiological in origin



Applying Machine Learning

Needed Elements

01 **Raw Data**

Partitioned MRI spectra
ie. Fourier transform data

02 **Output details**

Pre-defined classification results

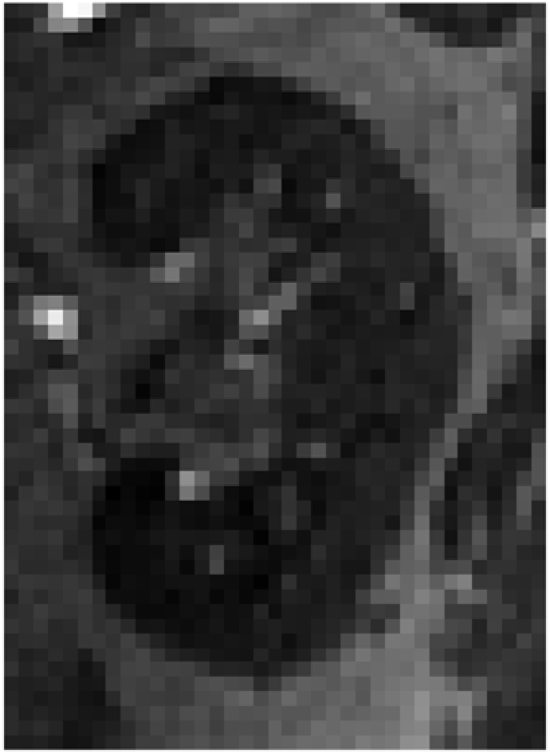
03 **ML Model**

Random forest

04 **Testing data**

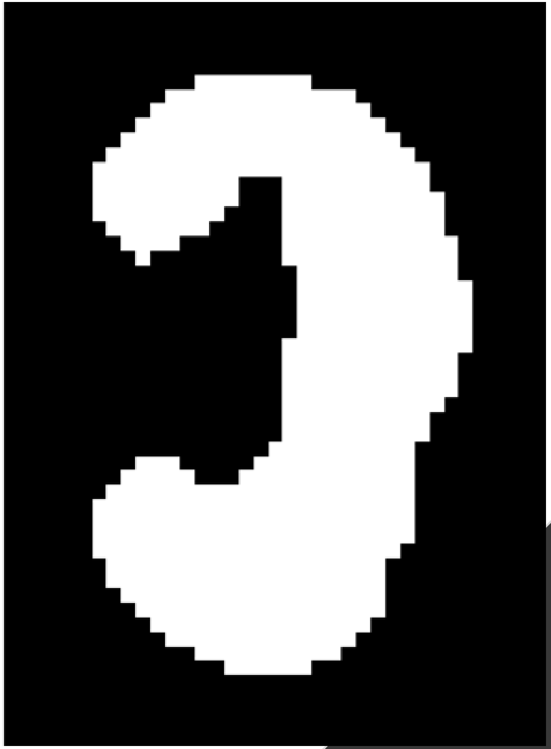
Remaining MR spectra

Cleaning up data

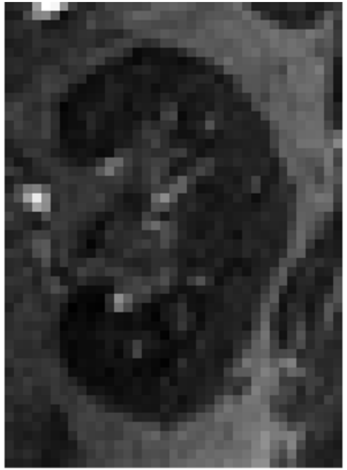


Edge detection filters & functions

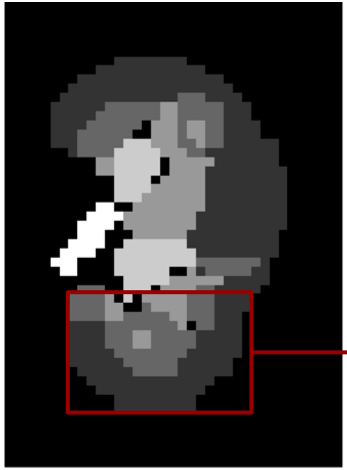
All black voxels have spectra zeroed



Output Details

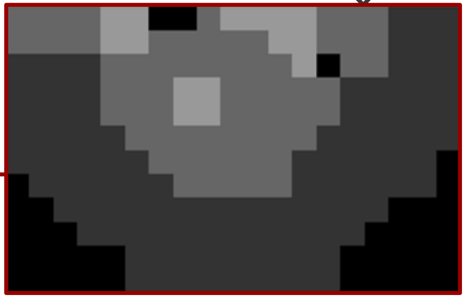


Original Image



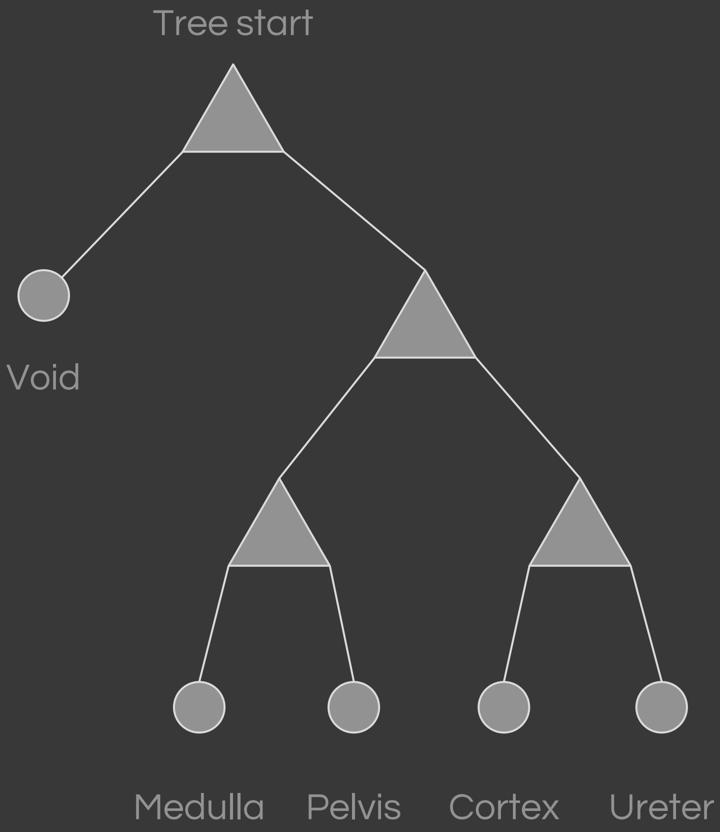
Pre - Defined Mask

Educated guess of
cortex, medulla, pelvis, vessels, &
ureter



Training Section

Ureter & pelvis excluded



How Random Forest Works

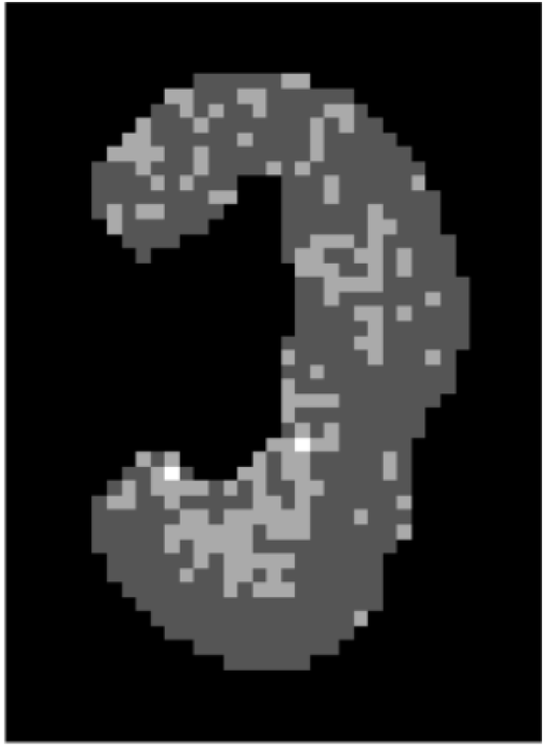
- Feed test data & results
- Generate decision trees
  - Series of if/else statements
- ‘Prunes’ by limiting branch and decision nodes
- Advantageous for low amounts of testing data

The Final Step

- After the model is trained it is fed the remainder of the spectral data
  - Post-edge detection

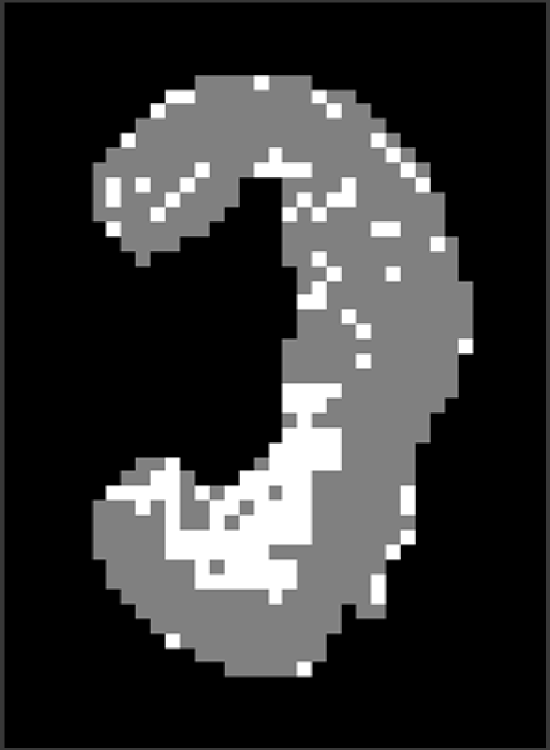
- Predicts what part of the kidney each voxel belongs to

Results



Parameter
Combination 1

Parameter
Combination 2



Potential improvements

- More accurate mask
  - Utilize contrast fluid to eliminate guesswork
- More time training
- Different hyperparameter ranges
- Edge Detection Improvements
- Interlaced ML predictors
  - Spectra varies depending on upper/lower/mid kidney

References

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