# cs231n Project Proposal - MRNet

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## 1. What is the problem that you will be investigating? Why is it interesting?

I will attempt to reproduce and extend the work done in "Deep-learning-assisted diagnosis for knee magnetic resonance imaging: Development and retrospective validation of MRNet", in which the researchers use deep learning to detect abnormalities in knee MRIs (Bien et al., 2018).

Reading and interpreting MRIs is a time-consuming process that requires trained professionals. Improving the automated identification of abnormalities in knee MRIs could help prioritize which MRIs to examine first, as well as provide better early results for patients whose scans appear normal. The model predictions could also provide a "second opinion" which would reduce the possibility of missed abnormalities. This could represent a large cost savings for hospitals and an increased level of care for patients.

## 2. What reading will you examine to provide context and background?

See reference list.

## 3. What data will you use?

I will use the data and code provided in the MRNet challenge. The data contains scans from 3 MRI types (sagittal plane T2, coronal plane T1, and axial plane PD) with 3 labels per MRI (abnormality, ACL tear, and meniscal tear) for 1,370 examinations.

## 4. What method or algorithm are you proposing?

Bien, et al. used a pretrained AlexNet model trained on ImageNet to extract features from the MRI slices, followed by several pooling layers and a fully connected layer (Bien et al., 2018). I will attempt to reproduce their results, and then experiment with different ways of extending their architecture. I will try using other pretrained models for feature extraction, including VGG (Simonyan & Zisserman, 2014) and ResNet (He et al., 2016). I would also like to experiment with running 3D convolutions over the slices, rather than just pooling. Another potential avenue of research would be to ensemble the 3 MRI-type models at the feature level, rather than training a logistic regression over the specific MRI-type model predictions.

## 5. How will you evaluate your results?

### 5.1. Qualitatively, what kind of results do you expect (e.g. plots or figures)?

Plots of the ROC curve for each model (one per MRI type and task) and ensemble (one per task).

### 5.2. Quantitatively, what kind of analysis will you use to evaluate and/or compare your results (e.g. what performance metrics or statistical tests)?

I will measure the sensitivity, specificity, accuracy, and AUC for the models under each task (abnormality, ACL tear, and meniscal tear), both before and after ensembling.

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## References

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