# COLITIS DETECTION ON COMPUTED TOMOGRAPHY USING REGIONAL CONVOLUTIONAL NEURAL NETWORKS

Jiamin Liu, David Wang, Zhuoshi Wei, Le Lu, Lauren Kim, Evrim Turkbey, Ronald M. Summers

Imaging Biomarkers and Computer-aided Diagnosis Laboratory
Radiology and Imaging Sciences, National Institutes of Health Clinical Center
Building 10 Room 1C224 MSC 1182, Bethesda, MD 20892-1182

## ABSTRACT

Colitis is inflammation of the colon that is frequently associated with infection and immune compromise. The wall of a colon afflicted with colitis is much thicker than normal. Colitis can be debilitating or life threatening, and early detection is essential to initiate proper treatment. In this work, we apply high-capacity convolutional neural net-works (CNNs) to bottom-up region proposals to detect potential colitis on CT scans. Our method first generates around 3000 category-independent region proposals for each slice of the input CT scan using selective search. Then, a fixed-length feature vector is extracted from each region proposal using a CNN. Finally, each region proposal is classified and assigned a confidence score with a linear SVM. We applied the detection method to 448 images from 56 CT scans of patients with colitis for evaluation. The detection system achieved 85% sensitivity at 1 false positive per image.

***Index Terms*** – Colitis, Region proposal, CNNs, SVM

## 1. INTRODUCTION

Colitis is a potentially debilitating and life-threatening inflammation of the inner lining of the colon and often results in abdominal pain and diarrhea. Abdominal computed tomography (CT) is commonly used to diagnose patients that present with these symptoms. Common causes of colitis include viral or bacterial infection, ischemia, or inflammatory bowel disease.

Colitis is characterized by a thickening of the colon wall, and while the colon wall thickness varies depending on lumen distention, a wall thickness of greater than 3 mm is often considered a clinical abnormality [1]. In a study of CT scans used in differential diagnosis, the average thickness of the colon wall was found to be 11.0 mm in patients with Crohn's Disease and 7.8 mm in those with ulcerative colitis [2]. Another indicator of possible colitis in abdominal CT images is an "accordion sign" seen in images of patients who have taken oral contrast material, indicating thickening of edematous haustral folds [3]. Figure 1 shows examples of colon with wall thickening (10.6 mm) and accordion pattern on patients' CT scans with colitis. These appearance indicators are important for computer-aided colitis detection.

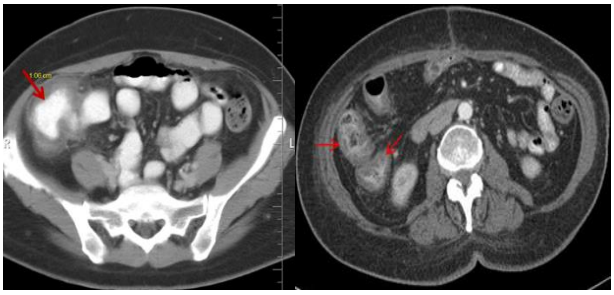


Figure 1. (a) Colitis of the cecum (most proximal part of the colon) with 10.6 mm wall thickening. (b) Colitis of the ascending colon with accordion pattern.

Early detection of colitis is crucial to early intervention that lessens duration and severity of the ailment [4]. In the current clinical workflow, each CT image is manually examined to detect instances of colitis, a relatively tedious and inefficient process.

Image descriptors such as SIFT [5] and HOG [6] have been widely used for object detection and recognition. A recent work [7] shows that convolutional neural networks (CNNs) can provide more informative features for visual recognition.

CNNs have been successfully applied to many medical applications, such as mitosis detection in breast histology images [8], lymph node detection in CT images [9], pancreas segmentation in CT images [10], and brain MR image segmentation [11].

In this work, we propose a fully automated method for colitis detection in CT images using regional convolutional neural network (R-CNN) [12]. In R-CNN, high-capacity CNNs and bottom-up region proposals are combined for more accurate object detection.

## 2. METHODS

Our system for detecting colitis includes three major steps: (1) Category-independent region proposals are generated for each input image. These proposals are candidates for colitis detection. (2) For each region proposal, a fixed-length feature vector is computed using a large convolutional neural network. (3) A linear Support Vector Machine (SVM) is used for colitis classification. Figure 2 shows the overview of our colitis detection system.

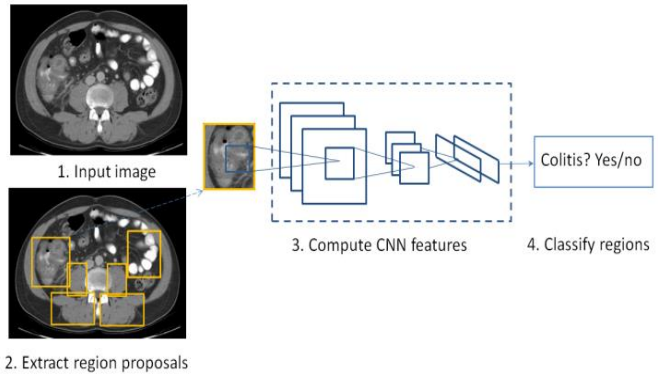



Figure 2. Colitis detection system overview.

### 2.1 Region proposals

Many recent works such as objectness [13], edge boxes [14], and constrained parametric min-cuts [15] are proposed for generating category-independent region proposals. Considering the computation accuracy and efficiency, we use selective search [16] to generate region proposals in this work. Selective search combines the strength of exhaustive search and segmentation methods. In this work, an efficient graph-based segmentation method [17] is utilized to get initial regions. A hierarchical grouping algorithm [16] is then iteratively group regions together.

In our implementation, there are about 3000 region proposals for each input image (one slice of a CT volume). Figure 3 shows some examples of generated region proposals. These region proposals are structure meaningful, such as colon (Fig. 3a), kidney (Fig. 3b), muscle (Fig. 3c and Fig. 3e), vertebra (Fig. 3d) and colitis (Fig. 3f).

### 2.2 Feature computation

For each region proposal, a 4096-dimensional feature vector is extracted using the Caffe [18] implementation of the AlexNet CNN [19]. That is, features are computed through 7 hidden layers (five convolutional layers and two fully connected layers). This AlexNet is pre-trained on the PASCAL 2007 dataset [20].

In this work, the AlexNet architecture requires inputs of 227×227 pixel size. Thus, we warp the region proposal into the required size to compute features. The region proposal is dilated to include contextual information before warping.

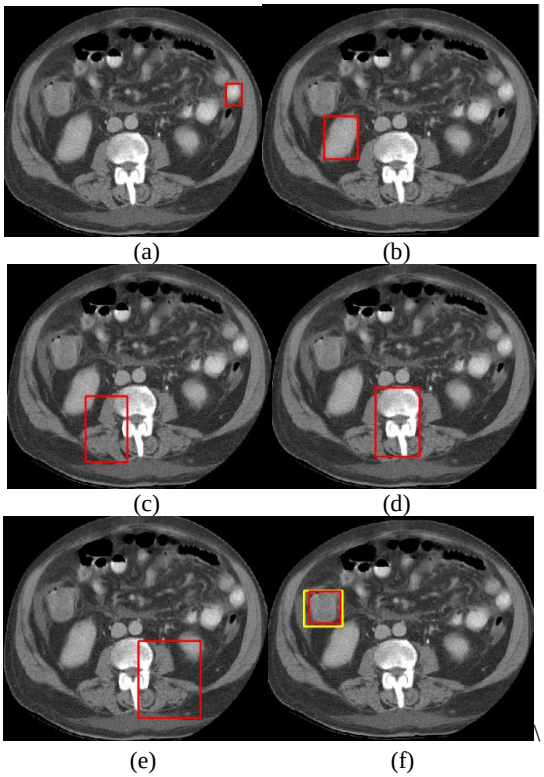



Figure 3. Examples of generated region proposals (Red boxes) and manually labeled colitis (Yellow box).

### 2.3 Colitis classification

During training, all ground-truth bounding boxes enclosing the manually labeled colitis are used as positive samples. The region proposals which have an intersection-over-union (IoU) overlap with a ground-truth box lower than 0.3 are defined as negative samples. A linear SVM is optimized with the features computed from CNN and training labels for colitis classification.

During testing, selective search is run on the test image and around 3000 region proposals are extracted. Each proposal is warped to the required size and forward propagated through the AlexNet CNN for feature computation. Then, the trained SVM is applied and the extracted feature vectors are scored. The region proposals with higher score are classified as detected colitis.

### 2.4 Bounding-box regression

We also apply a bounding-box regression [12] to correct the mis-localizated region proposals and to further improve the detection performance. After SVM scoring, a new bounding box is predicted using the bounding-box regressor. That is, using the features computed from the

AlexNet CNN, a transformation is learned to map a region proposed bounding box to a ground-truth bounding box. Figure 4 shows some examples of bounding boxes before and after the regression. The bounding boxes after the regression are almost identical to the ground-truth bounding boxes.

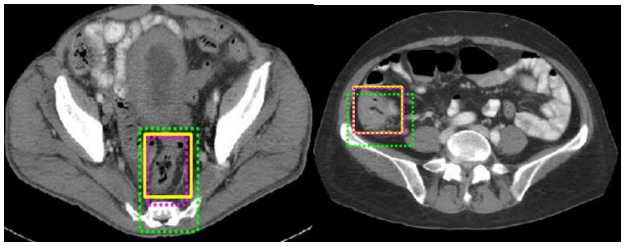


Figure 4. Examples of generated region proposals (Green bounding boxes), detections after bounding regression (Pink bounding boxes) and manually labeled colitis (Yellow bounding boxes).

## 3. RESULTS

CT scans of 56 patients with colitis are used to develop and evaluate our detection system. For each patient, 8 images with radiologists marked colitis are selected. Thus, our dataset has 448 images with labeled colitis in total. 90% of 448 (404) images are randomly selected for the training set and the remaining 44 images are assigned to the test set for evaluation. For each image, one or more bounding boxes enclosing the colitis region are manually labeled by a radiologist as ground-truth.

The recall of colitis detection on the test images is 98% after the region proposal generation. The average detection precision is 69% before the bounding-box regression is applied. With the regression, the average detection precision is increased to 73%.

The detections which have an IoU overlap with a ground-truth box more than 0.5 are considered as true positive detections. Figure 5 shows the FROC curves of colitis detection on 44 test images. At 1 false positive per image, the system achieves sensitivities of 82% and 85% before and after bounding-box regression, respectively.

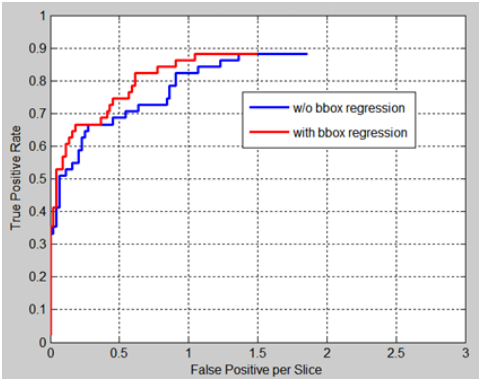



Figure 5. FROC curves of colitis detection on test set.

Figure 6 shows some true positive detections and their corresponding ground-truth boxes.

False positive detections (IoU less than 0.5) are shown in in Figure 7. Normal colon with stool (Fig. 7a and 7b), kidney (Fig. 7c) and liver (Fig. 7d) are mis-detected as colitis since their 2D appearances are similar to colitis to some extent. R-CNN based multi-class detector including liver, normal colon, kidney, and muscle detection could improve colitis detection performance by reducing false positives. The idea is that these false positives could be correctly detected as other classes such as kidney with a higher score and then removed from the colitis detections.

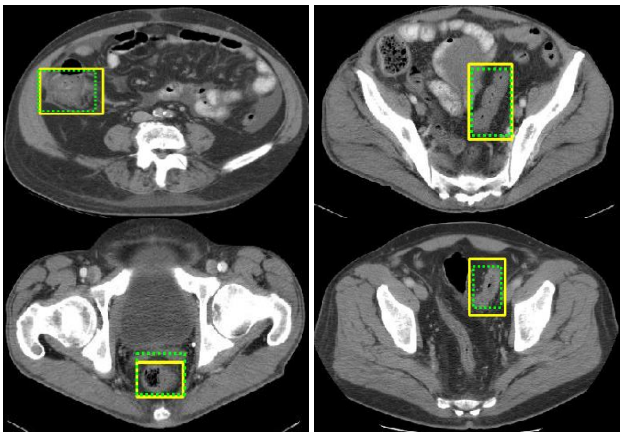
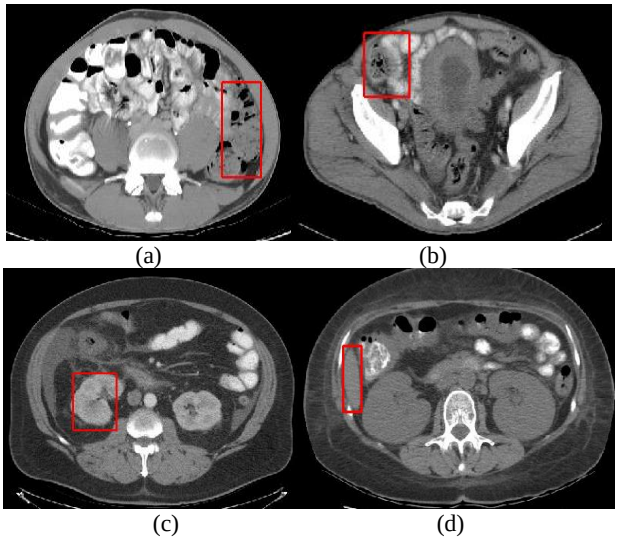


Figure 6. Examples of detected colitis (Green) and the ground-truth boxes (Yellow).



(a) (b)

(c) (d)

Figure 7. Example of false positive detections: normal colon with stool (a, b), kidney (c) and liver (d).

## 4. CONCLUSION

In this work, high-capacity convolutional neural networks and bottom-up region proposals are applied for

colitis detection on CT images. The region proposals are first generated by selective search and features are extracted with convolutional neural networks. With these high level CNN features, a linear SVM classifier is optimized for colitis classification. The experimental results show a high sensitivity (85%) at a low false positive rate (1 per image) which may be clinically acceptable.

**Acknowledgments**

This research was supported by the National Institutes of Health, Clinical Center.

**REFERENCES**

1. Macari, M. and E.J. Balthazar, "CT of bowel wall thickening: Significance and pitfalls of interpretation," American Journal of Roentgenology,176,1105-1116(2001).
2. Philpotts, L.E., J.P. Heiken, M.A. Westcott, and R.M. Gore, "Colitis - Use of Ct Findings in Differential-Diagnosis," Radiology,190,445-449(1994).
3. O'Sullivan, S.G., "The accordion sign," Radiology,206,177-178(1998).
4. Van Assche, G., A. Dignass, B. Bokemeyer, S. Danese, P. Gionchetti, G. Moser, L. Beaugerie, F. Gomollon, W. Hauser, K. Herrlinger, B. Oldenburg, J. Panes, F. Portela, G. Rogler, J. Stein, H. Tilg, S. Travis, J.O. Lindsay, and Ecco, "Second European evidence-based consensus on the diagnosis and management of ulcerative colitis Part 3: Special situations," Journal of Crohns & Colitis,7,1-33(2013).
5. Lowe, D.G., "Distinctive image features from scale-invariant keypoints," International Journal of Computer Vision,60,91-110(2004).
6. Dalal, N. and B. Triggs, "Histograms of oriented gradients for human detection," 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, Vol 1, Proceedings,886-893(2005).
7. Bengio, Y., A. Courville, and P. Vincent, "Representation Learning: A Review and New Perspectives," Ieee Transactions on Pattern Analysis and Machine Intelligence,35,1798-1828(2013).
8. Ciresan, D.C., A. Giusti, L.M. Gambardella, and J. Schmidhuber, "Mitosis Detection in Breast Cancer Histology Images with Deep Neural Networks," Medical Image Computing and Computer-Assisted Intervention - Miccai 2013, Pt Ii,8150,411-418(2013).
9. Roth, H., L. Le, S. Ari, C.K. M, H. Joanne, W. Shijun, L. Jiamin, T. Evrim, and S.R. M. A new 2.5D representation for lymph node detection in CT. 2014; Available from: https://wiki.cancerimagingarchive.net/display/DOI/A+new+2.5D+representation+for+lymph+node+detection+in+CT.
10. Roth, H.R., A. Farag, L. Lu, E.B. Turkbey, and R.M. Summers, "Deep convolutional networks for pancreas segmentation in CT imaging," Medical Imaging 2015: Image Processing,9413,(2015).
11. Zhang, W.L., R.J. Li, H.T. Deng, L. Wang, W.L. Lin, S.W. Ji, and D.G. Shen, "Deep convolutional neural networks for multi-modality isointense infant brain image segmentation," Neuroimage,108,214-224(2015).
12. Girshick, R., J. Donahue, T. Darrell, and J. Malik, "Rich feature hierarchies for accurate object detection and semantic segmentation," 2014 Ieee Conference on Computer Vision and Pattern Recognition (Cvpr),580-587(2014).
13. Alexe, B., T. Deselaers, and V. Ferrari, "Measuring the Objectness of Image Windows," Ieee Transactions on Pattern Analysis and Machine Intelligence,34,2189-2202(2012).
14. Zitnick, C.L. and P. Dollar, "Edge Boxes: Locating Object Proposals from Edges," Computer Vision - Eccv 2014, Pt V,8693,391-405(2014).
15. Carreira, J. and C. Sminchisescu, "CPMC: Automatic Object Segmentation Using Constrained Parametric Min-Cuts," Ieee Transactions on Pattern Analysis and Machine Intelligence,34,1312-1328(2012).
16. Uijlings, J.R.R., K.E.A. van de Sande, T. Gevers, and A.W.M. Smeulders, "Selective Search for Object Recognition," International Journal of Computer Vision,104,154-171(2013).
17. Felzenszwalb, P.F. and D.P. Huttenlocher, "Efficient graph-based image segmentation," International Journal of Computer Vision,59,167-181(2004).
18. Jia, Y. Caffe: An open source convolutional architecture for fast feature embedding. 2013; Available from: http://caffe.berkeleyvision.org/.
19. Krizhevsky, A., I. Sutskever, and G. Hinton. "ImageNet Classification with Deep Convolutional Neural Networks". in *NIPS*. 2012.
20. Everingham, M., L. Van Gool, C.K.I. Williams, J. Winn, and A. Zisserman, "The Pascal Visual Object Classes (VOC) Challenge," International Journal of Computer Vision,88,303-338(2010).