Person Detection using Faster-RCNN

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Abstract

Person detection has been a widely researched topic in the field of Computer Vision and Artificial Intelligence. It has multiple applications like target detection or traffic/crowd control. From image processing to deep learning, person detection techniques have improved both in accuracy and response time. This paper is an attempt to detect people from images using Faster-RCNN and replicate results of existing research. In order to verify advantages of deep learning techniques over HOG with SVM, a HOG-SVM model was built to run the test images on. Amongst deep learning approaches, while YOLO has proven to be the fastest, Faster-RCNN has been very accurate and computationally feasible for industrial approach.

Dataset

The INRIA person dataset was used for training and testing. The Penn-Fudan Database for Pedestrian Detection and Segmentation was used to augment the training data and make the model more robust.

Annotation

The images had been annotated as per the PASCAL VOC dataset format. Regex expression were run across each annotation file for an image and a JSON file was created which contained every filename along with the coordinates of the ground truth boxes. The json file was then used to create a text file with the following format:

Filepath,x1,y1,x2,y2,class_name
where,

- *filepath is the path of the training image*
- *x1 is the xmin coordinate for bounding box*
- *y1 is the ymin coordinate for bounding box*
- *x2 is the xmax coordinate for bounding box*
- *y2 is the ymax coordinate for bounding box*
- *class_name is the name of the class, i.e., human in that bounding box*

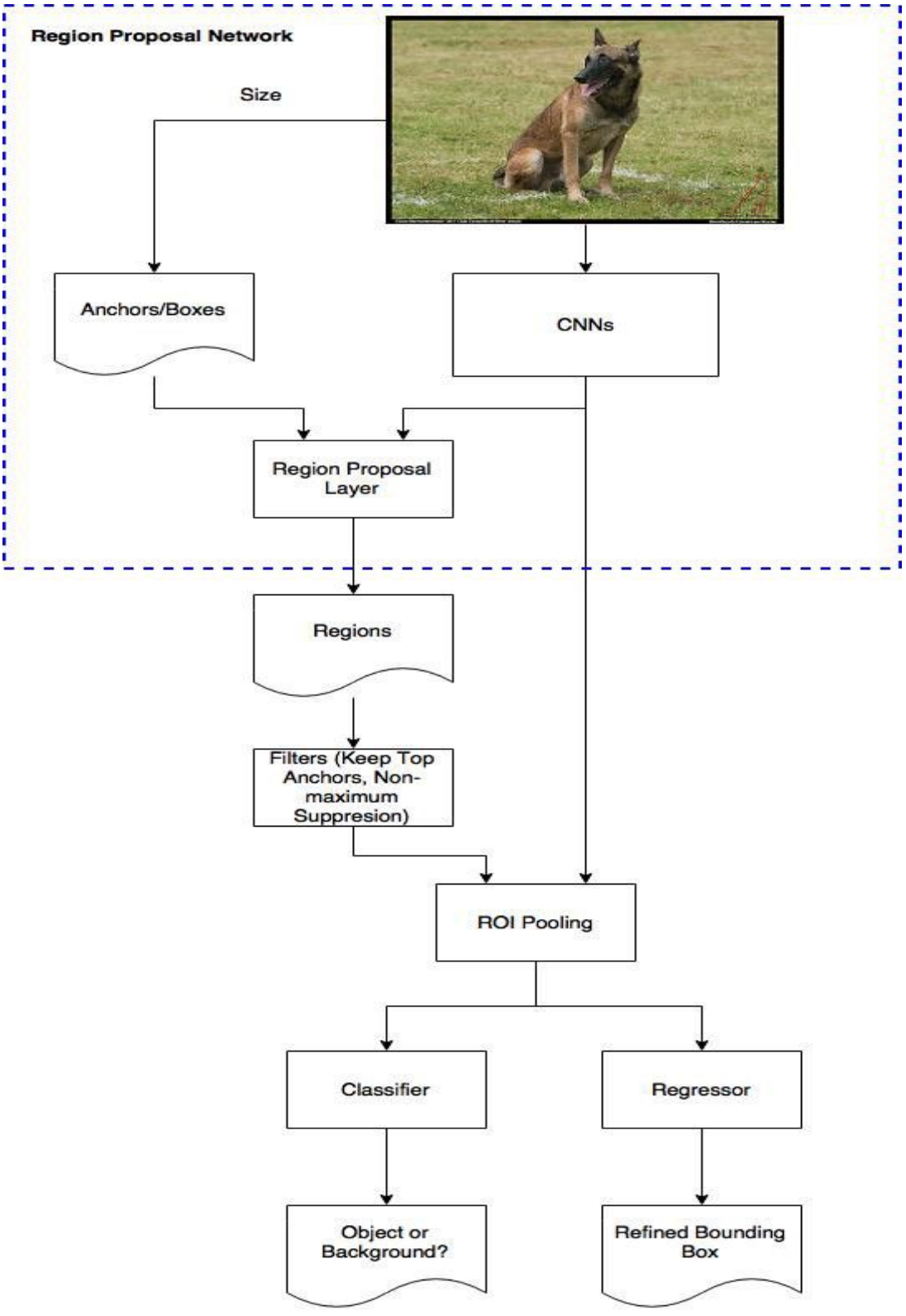
Pre-processing

- The shortest side of the image was resized to 600px
- All images were horizontally flipped for data augmentation
- Reducing image size led to loss of information and hence was not applied.
- Converting all images to grayscale also led to loss in accuracy and hence was not applied in the final dataset.

Methodology:

Faster-RCNN

- Take an input image and pass it to the ConvNet which returns feature maps for the image
- Apply Region Proposal Network (RPN) on these feature maps and get object proposals
- Apply ROI pooling layer to bring down all the proposals to the same size
- Finally, pass these proposals to a fully connected layer in order to classify any predict the bounding boxes for the image



Non-max suppression

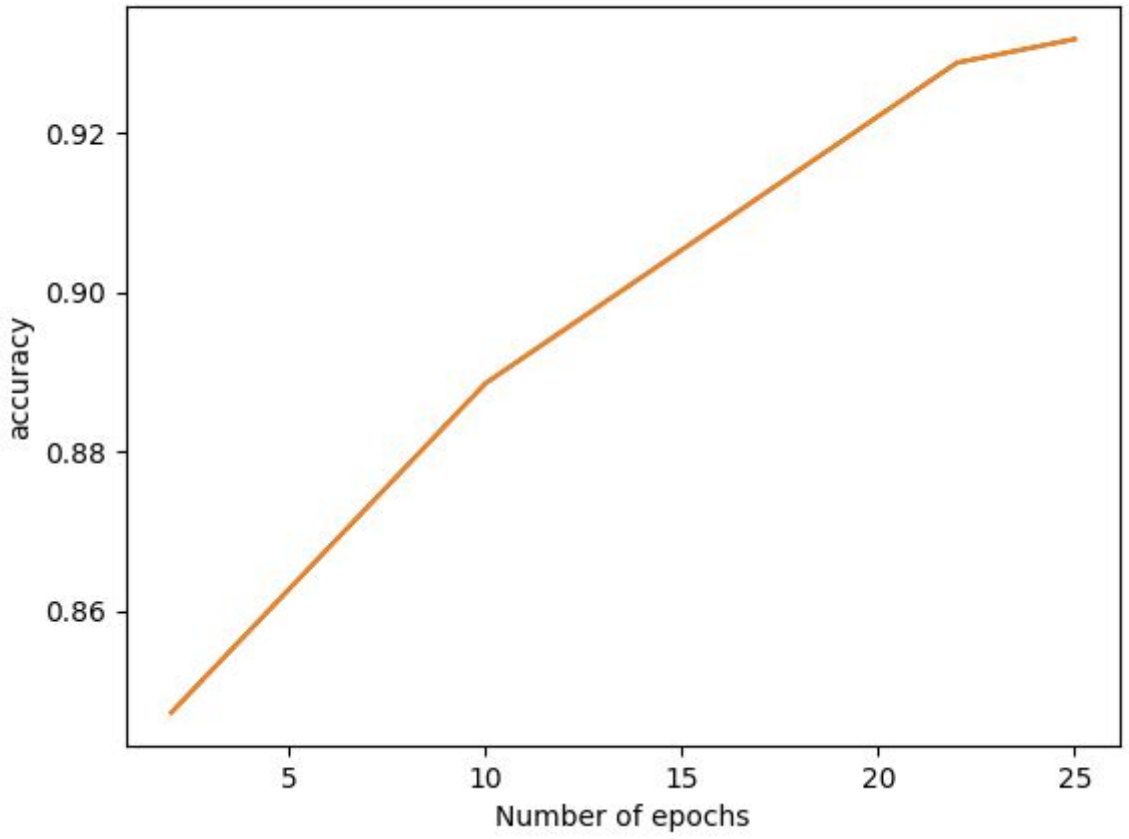
In-order to deal with overlapping bounding boxes, non-max suppression is applied.

Anchors

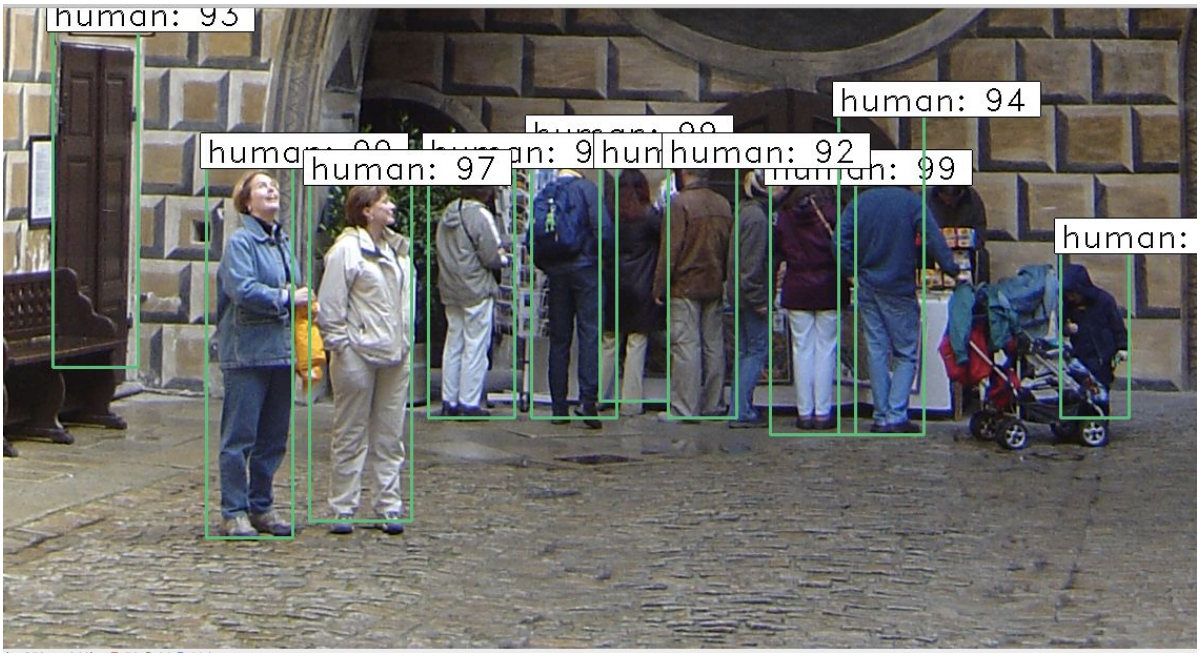
- Anchor scales used : 128x128, 256x256, 512x512
- Anchor ratios : 1:1, 1/√2:2/√2, 2:√2:1/√2
- Total number of anchors: 9
- Since stride taken was 16, at every 16 pixels, 9 anchor boxes were considered for occurence of object

Results

The accuracy of the RPN bounding box was : 93.17%
The following is the rate of growth of accuracy with the number of epochs:



The following are the classification results:



Future work

- A few of the training images had more than one person. Due to the annotation limitations, only one bounding box coordinates could be provided to the model. Since the model treats all the data outside the bounding box as negative samples, there might be the case that a few images of people were assumed to be negative sample. Such samples might have affected the accuracy of the model.
- I recently came across a paper[1] which provides the neural net training images after applying HOG on them to extract relevant features. I would like to try such preprocessing to my model.

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[1] Martinson, E., and V. Yalla. "Real-time human detection for robots using CNN with a feature-based layered pre-filter." *Robot and Human Interactive Communication (RO-MAN), 2016 25th IEEE International Symposium on*. IEEE, 2016.