3. Comparison to other Detection Systems

Generally speaking, computer vision and object detection require 2 main steps for successful implementation. Extracting features from the incoming images and then classifying them based on the data extracted are the main steps followed by different algorithms, and we will compare YOLO to current algorithms.

1- **Deformable Parts Model (DPM):** This object detection system uses a sliding window with separate steps to get the bounding boxes of high scores. Instead of static feature extraction, region classification, and bounding box prediction done separately as in DPM, the YOLO procedure replaces all that with a single convolutional neural network (CNN) that is optimized to extract features based on the application unlike the static feature extraction of DPM. This allows YOLO to be faster and more accurate in object detection.

2- **Region Based Convolutional Neural Networks (R-CNN):** This method uses proposed regions for the bounding box instead of sliding window. Selective search is used for generating the bounding boxes, followed by a CNN to extract features from the bounding boxes, support vector machine to give scores to the boxes, a linear model to adjust the bounding boxes, and non-max suppression to eliminate duplicate detections. This long-separated steps require independent fine tuning and takes more time (40 seconds at test time) to detect objects. R-CNN is similar to YOLO in the bounding box generation, but YOLO provides much fewer bounding boxes with minimal duplications and the whole process is joined in a single CNN.

3- **Other Fast Detectors (Fast, Faster R-CNN):** Fast and Faster R-CNN focus on speeding up the R-CNN framework by sharing computation and using neural networks to propose regions instead of Selective Search. These make the R-CNN much faster but still not enough for real time performance. Similarly, some proposed faster DPM by faster computation and GPU utilization, but only 30Hz DPM is suitable for real time operation. Compared to YOLO, which is fast by design and is considered a general-purpose detector that can be trained for a variety of applications like face detection.

4- **Deep MultiBox:** instead of selective search to get bounding boxes as in R-CNN, this approach trains a convolutional neural network to predict regions of interest and can perform single class prediction by using the confidence as a threshold. This approach is considered a single step in image object detection as further classification is needed after getting the bounding boxes.

5- **OverFeat:** This approach uses a CNN to perform localization from which object detection can be made. Like DPM, the localizer only sees local information when making a prediction. OverFeat cannot reason about global context and thus requires significant post-processing to produce coherent detections.

6- **MultiGrasp:** The YOLO approach is similar to MultiGrasp approach in the bounding box prediction based on the grid approach. Grasp detection done by MultiGrasp is a much simpler task compared to the Object detection done by YOLO in which object size, location, and boundaries are needed to predict the class. MultiGrasp works with images containing only one object and only finds region suitable for grasping, while YOLO predicts both bounding boxes and class probabilities for multiple objects of multiple classes.

4. Experiments

The dataset PASCAL VOC 2007 is used to compare the performance of YOLO and other detection methods. Studying the errors made by YOLO and Fast RCNN was also made to merge the two algorithms, thus boosting the overall performance. Also, VOC 2012 is used to test the performance of YOLO and its generalizability is tested on two artwork datasets.

4.1. Comparison to Other Real-Time Systems

Object detection algorithms need to be fast for real-time operation. For instance, the minimal accepted performance is to successfully process 30 images per second to be able to analyze a real-time video stream of 30FPS. The only systems with such performance are the DPM (30Hz, 100Hz) running on GPU and YOLO (Fast, Normal). Fast YOLO is the fastest known algorithm to detect objects in the Pascal VOC 2007,2012 Dataset with a speed of 155FPS and performance measured in "mean average precision" mAP of 52.7%. This performance metric is used with object detection algorithms to quantize the precision recall of each class averaged. Compared to YOLO, DPM detectors are of poor mAP and are not as fast as YOLO. However, YOLO is not of the highest mAP when we check detectors that can't work in real-time even with the increase of 10% in mAP when using YOLO compared to Fast YOLO. Different Fast RCNN are tested with different bounding box generation methods. RCNN Minus R uses static bounding box locations, while the conventional Fast RCNN uses selective search which is the slowest in the performed tests (taking 2 seconds per image). Using neural networks instead of selective search boosts speed up to 7FPS and using a smaller network of less accuracy bumps the speed of Fast RCNN into 18 FPS which is still less than the Real-time needed performance. The table shows performance and speed of different object detection algorithms and on which datasets are they trained. The VGG-16 version of Faster R-CNN is 10 mAP higher but is also 6 times slower than YOLO. The Zeiler- Fergus Faster R-CNN is only 2.5 times slower than YOLO but is also less accurate.

Real-Time Detectors	Train	mAP	FPS
100Hz DPM [31]	2007	16.0	100
30Hz DPM [31]	2007	26.1	30
Fast YOLO	2007+2012	52.7	**155**
YOLO	2007+2012	**63.4**	45
Less Than Real-Time			
Fastest DPM [38]	2007	30.4	15
R-CNN Minus R [20]	2007	53.5	6
Fast R-CNN [14]	2007+2012	70.0	0.5
Faster R-CNN VGG-16[28]	2007+2012	73.2	7
Faster R-CNN ZF [28]	2007+2012	62.1	18
YOLO VGG-16	2007+2012	66.4	21

Table 1: Real-Time Systems on PASCAL VOC 2007. Comparing the performance and speed of fast detectors. Fast YOLO is the fastest detector on record for PASCAL VOC detection and is still twice as accurate as any other real-time detector. YOLO is 10 mAP more accurate than the fast version while still well above real-time in speed.

4.2. VOC 2007 Error Analysis

The study of errors in the detection algorithms is used to identify the weak points of each detection system and how to overcome them by combining different models together. To study the error, the following classification of model results is used:

- Correct: class is correct, and Intersection over union (IOU) is greater than 0.5.
- Localization: class is correct, and IOU is greater than 0.1 but less than 0.5.
- Similar: class is similar, and IOU is greater than 0.1.
- Other: class is wrong, and IOU is greater than 0.1.
- Background: for all IOU less than 0.1.

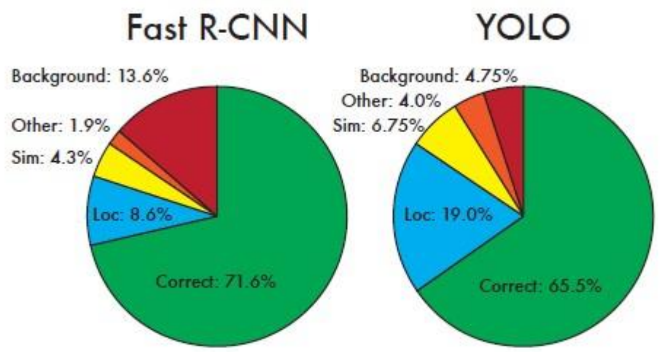


Figure 4: Error Analysis: Fast R-CNN vs. YOLO These charts show the percentage of localization and background errors in the top N detections for various categories (N = # objects in that category).

Notice that Fast RCNN had a higher correct percentage than YOLO, but as we have seen earlier this higher mAP is paid for in performance speed. The YOLO system had most of its not correct classifications as localization errors (which means the system got the class correct but couldn't accurately determine its position in the image). Also, Fast RCNN had a large background error which are false positives with no object in the image. Notice that from this error analysis we can see that if we use Fast RCNN first, then used YOLO to correct the results of the Fast RCNN, we will boost the accuracy of this model greatly as seen in the next section.

4.3. Combining Fast RCNN and YOLO

For every bounding box that R-CNN predicts, YOLO is used to check if it predicts a similar box. If it does, that prediction takes a boost based on the probability predicted by YOLO and the overlap between the two boxes. The best Fast R-CNN model achieves a mAP of 71.8% on the VOC 2007 test set. When combined with YOLO, its mAP increases by 3.2% to 75.0%. This boost is performance is not just a conventional ensemble because YOLO has errors in different categories from those made by Fast RCNN, so YOLO rectifies the errors made by Fast RCNN. This approach however does not benefit from the speed of YOLO as Fast RCNN is run first and then YOLO is applied separately.

4.4. VOC 2012 Results

On this dataset, the YOLO algorithm has a mAP of 57.9% which is considered low compared to other current object detection algorithms. This reduction in mAP is justified when each Average Precision is calculated for each class alone. It is noted that YOLO struggles with smaller objects compared to other algorithms like Faster RCNN. On categories like *bottle*, *sheep*, and *tv/monitor* YOLO scores 8-10% lower than R-CNN or Feature Edit. However, on other categories like *cat* and *train* YOLO achieves higher performance.

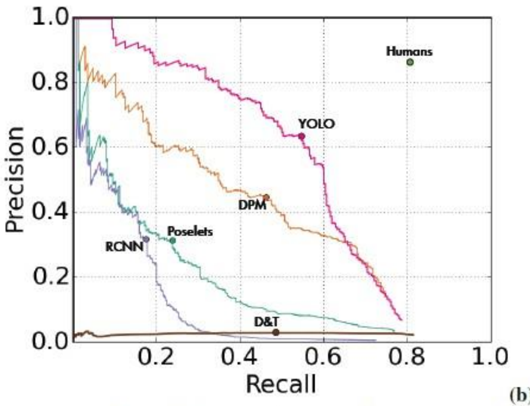
When we combine YOLO and Fast RCNN, this model is boosting the performance of Fast RCNN with 2.3% and is considered one of the top 4 performing detection methods.

VOC 2012 test	mAP	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv
MR_CNN_MORE_DATA [11]	**73.9**	**85.5**	**82.9**	**76.6**	**57.8**	**62.7**	**79.4**	77.2	86.6	**55.0**	**79.1**	**62.2**	87.0	**83.4**	**84.7**	78.9	45.3	73.4	65.8	80.3	74.0
HyperNet_VGG	71.4	84.2	78.5	73.6	55.6	53.7	78.7	**79.8**	87.7	49.6	74.9	52.1	86.0	81.7	83.3	**81.8**	**48.6**	**73.5**	59.4	79.9	65.7
HyperNet_SP	71.3	84.1	78.3	73.3	55.5	53.6	78.6	79.6	87.5	49.5	74.9	52.1	85.6	81.6	83.2	81.6	48.4	73.2	59.3	79.7	65.6
Fast R-CNN + YOLO	70.7	83.4	78.5	73.5	55.8	43.4	79.1	73.1	**89.4**	49.4	75.5	57.0	**87.5**	80.9	81.0	74.7	41.8	71.5	68.5	**82.1**	67.2
MR_CNN_S_CNN [11]	70.7	85.0	79.6	71.5	55.3	57.7	76.0	73.9	84.6	50.5	74.3	61.7	85.5	79.9	81.7	76.4	41.0	69.0	61.2	77.7	72.1
Faster R-CNN [28]	70.4	84.9	79.8	74.3	53.9	49.8	77.5	75.9	88.5	45.6	77.1	55.3	86.9	81.7	80.9	79.6	40.1	72.6	60.9	81.2	61.5
DEEP_ENS_COCO	70.1	84.0	79.4	71.6	51.9	51.1	74.1	72.1	88.6	48.3	73.4	57.8	86.1	80.0	80.7	70.4	46.6	69.6	**68.8**	75.9	71.4
NoC [29]	68.8	82.8	79.0	71.6	52.3	53.7	74.1	69.0	84.9	46.9	74.3	53.1	85.0	81.3	79.5	72.2	38.9	72.4	59.5	76.7	68.1
Fast R-CNN [14]	68.4	82.3	78.4	70.8	52.3	38.7	77.8	71.6	89.3	44.2	73.0	55.0	**87.5**	80.5	80.8	72.0	35.1	68.3	65.7	80.4	64.2
UMICH_FGS_STRUCT	66.4	82.9	76.1	64.1	44.6	49.4	70.3	71.2	84.6	42.7	68.6	55.8	82.7	77.1	79.9	68.7	41.4	69.0	60.0	72.0	66.2
NUS_NIN_C2000 [7]	63.8	80.2	73.8	61.9	43.7	43.0	70.3	67.6	80.7	41.9	69.7	51.7	78.2	75.2	76.9	65.1	38.6	68.3	58.0	68.7	63.3
BabyLearning [7]	63.2	78.0	74.2	61.3	45.7	42.7	68.2	66.8	80.2	40.6	70.0	49.8	79.0	74.5	77.9	64.0	35.3	67.9	55.7	68.7	62.6
NUS_NIN	62.4	77.9	73.1	62.6	39.5	43.3	69.1	66.4	78.9	39.1	68.1	50.0	77.2	71.3	76.1	64.7	38.4	66.9	56.2	66.9	62.7
R-CNN VGG BB [13]	62.4	79.6	72.7	61.9	41.2	41.9	65.9	66.4	84.6	38.5	67.2	46.7	82.0	74.8	76.0	65.2	35.6	65.4	54.2	67.4	60.3
R-CNN VGG [13]	59.2	76.8	70.9	56.6	37.5	36.9	62.9	63.6	81.1	35.7	64.3	43.9	80.4	71.6	74.0	60.0	30.8	63.4	52.0	63.5	58.7
YOLO	57.9	77.0	67.2	57.7	38.3	22.7	68.3	55.9	81.4	36.2	60.8	48.5	77.2	72.3	71.3	63.5	28.9	52.2	54.8	73.9	50.8
Feature Edit [33]	56.3	74.6	69.1	54.4	39.1	33.1	65.2	62.7	69.7	30.8	56.0	44.6	70.0	64.4	71.1	60.2	33.3	61.3	46.4	61.7	57.8
R-CNN BB [13]	53.3	71.8	65.8	52.0	34.1	32.6	59.6	60.0	69.8	27.6	52.0	41.7	69.6	61.3	68.3	57.8	29.6	57.8	40.9	59.3	54.1
SDS [16]	50.7	69.7	58.4	48.5	28.3	28.8	61.3	57.5	70.8	24.1	50.7	35.9	64.9	59.1	65.8	57.1	26.0	58.8	38.6	58.9	50.7
R-CNN [13]	49.6	68.1	63.8	46.1	29.4	27.9	56.6	57.0	65.9	26.5	48.7	39.5	66.2	57.3	65.4	53.2	26.2	54.5	38.1	50.6	51.6

Table 3: PASCAL VOC 2012 Leaderboard. YOLO compared with the full comp4 (outside data allowed) public leaderboard as of November 6th, 2015. Mean average precision and per-class average precision are shown for a variety of detection methods. YOLO is the only real-time detector. Fast R-CNN + YOLO is the forth highest scoring method, with a 2.3% boost over Fast R-CNN.

4.5. Generalizability: Person Detection in Artwork

Because real life scenarios can lead the detection algorithm to deal with images from a different source than its training dataset, this section deals with testing detection algorithms on new artwork data different from the VOC 2007 dataset previously trained. Picasso Dataset and People-Art Dataset are used in this testing.



(a) Picasso Dataset precision-recall curves.

	VOC 2007 AP	Picasso AP	Picasso Best F_1	People-Art AP
YOLO	**59.2**	**53.3**	**0.590**	**45**
R-CNN	54.2	10.4	0.226	26
DPM	43.2	37.8	0.458	32
Poselets [2]	36.5	17.8	0.271	
D&T [4]	-	1.9	0.051	

(b) Quantitative results on the VOC 2007, Picasso, and People-Art Datasets. The Picasso Dataset evaluates on both AP and best F_1 score.

Figure 5: Generalization results on Picasso and People-Art datasets.

The preceding figure shows that although RCNN had a high AP on VOC 2007-person classification, its performance reduced dramatically on the Picasso dataset. This happened due to the RCNN usage of selective search which is more suited to natural images and not person detection as the bounding boxes proposed do not capture the whole person and only sees a small region at a time. DPM has a minimal degradation in AP because of its spatial feature preservation but already starts with a low AP in the VOC 2007 dataset. YOLO on the other hand had good performance on VOC 2007 and with minimal degradation when applied to artwork datasets. YOLO models the size and shape of objects, as well as relationships between objects and where objects commonly appear.

5. Real-Time Detection in the Wild

Although YOLO is an image-based object detection system, because of its fast and accurate detection, it can be used in computer vision as the camera captures a video stream from which images are extracted and processed by YOLO. This provides an interactive tracking system because of the fast response of the YOLO algorithm.

6. Conclusion

YOLO, the object detection system designed to be fast and easy to train directly on full images, is trained on a loss function that directly corresponds to detection performance and the entire model is trained jointly, unlike classifier-based approaches of separate modules. A faster version of YOLO (Fast YOLO) is proven to be the fastest object detector although with a reduction in its accuracy compared to YOLO. “You only look once” is the intuitive approach to object detection as it also generalizes well to new domains of data from other sources than that of training.

Paraphrasing Made by: Hamdy Osama (2100966)

Full Paper Review will be published when all team members submit their paraphrasing