P. Deschênes-Labrie, F. Qiang, K. Haddad, L. Duc Thien, N. Carl, J. Alejandro, W. Yizhe, X. Maldague

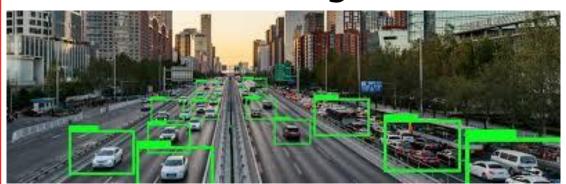


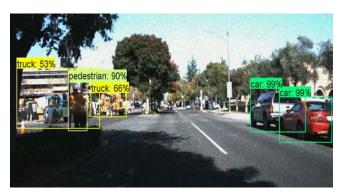


Outline:

- 1) Surface defect: Etch defect
- 2) Deep learning from CNN to Faster R-CNN
- 3) Results
- 4) Pros & Cons
- 5)Recommendation
- 6) Conclusion

Machine learning on vision

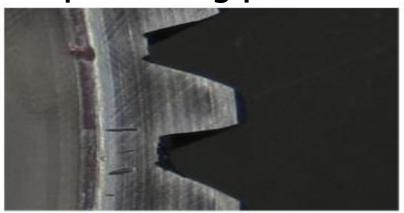


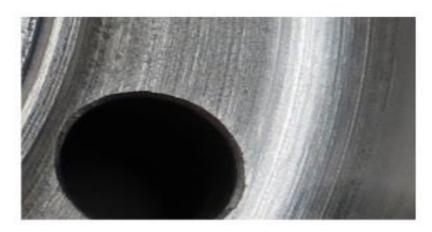


Advantages

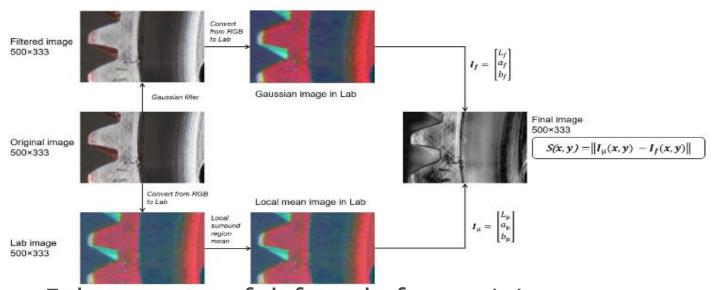
- Effective at solving problems: bounding boxes
- More data equals more accuracy and more stability compared to manual testing
- Faster to implement than classic computer vision
 - Challenges
- Dataset
- Etches is different: pixel level -> harder to detect

Preprocessing phase





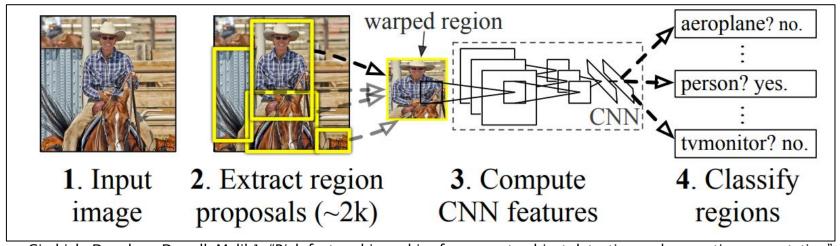
Defects may be clearly observed or ambiguous



Enhancement of defects before training

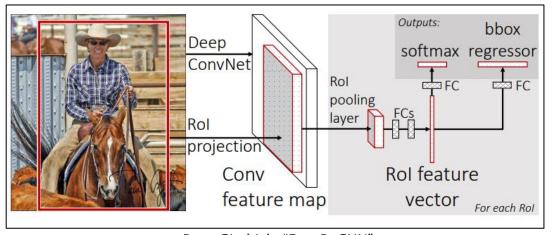
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▶ R-CNN



Girshick, Donahue, Darrell, Malik1, "Rich feature hierarchies for accurate object detection and semantic segmentation"

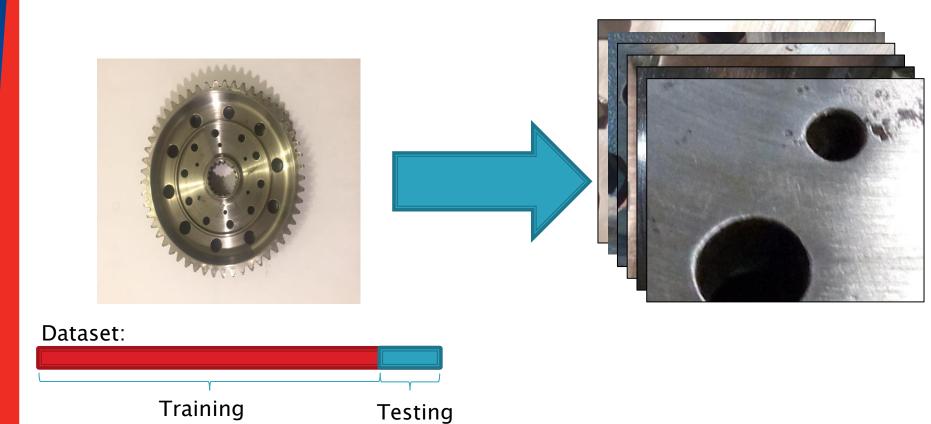
Faster R-CNN



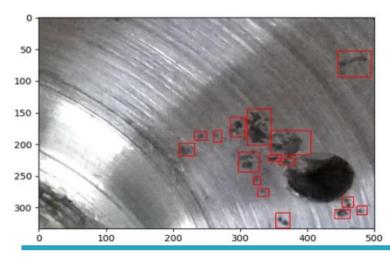
Ross Girshick, "Fast R-CNN"

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Dataset building



Defect detection proposalsRegion proposals



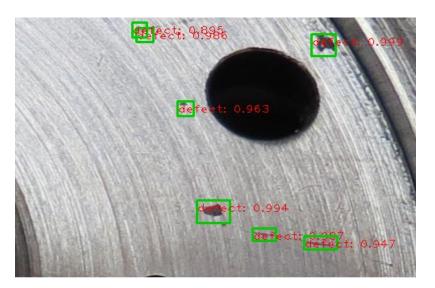
- Building from 4 cameras
- Hand marking one type of defect using bounding box
- Same part used for all the dataset

Programs

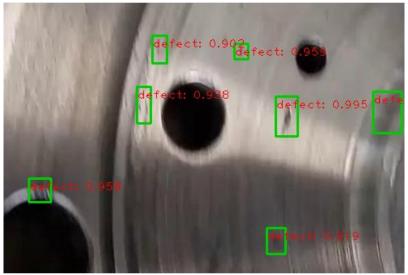


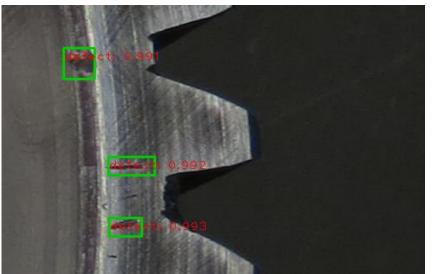
- Anaconda
- Package : DeepLearning Caffe
- Pascal VOC
- Python PyTorch & CUDA

Results



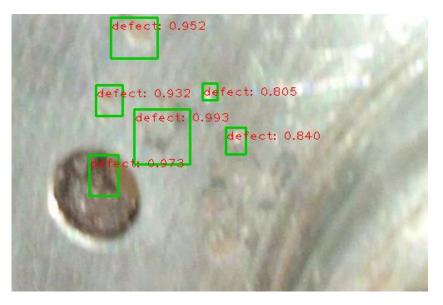


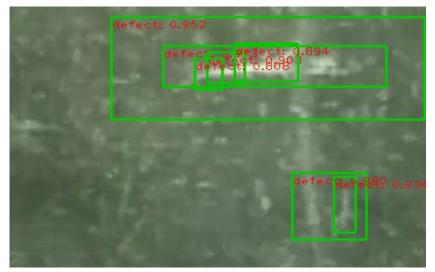


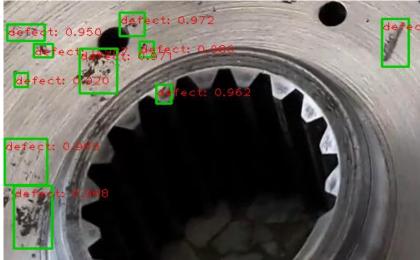


Results







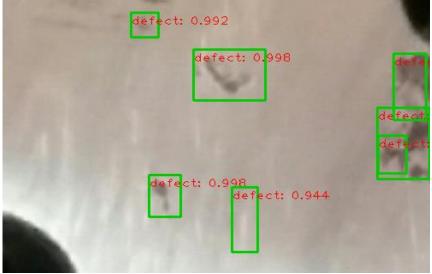


Results









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Results: Confusion Matrix

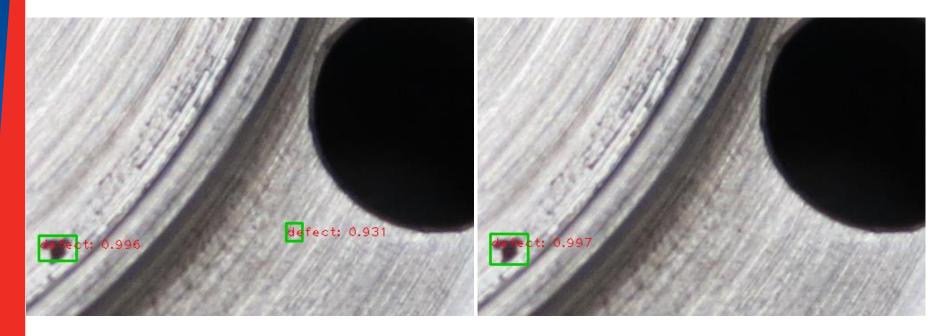
Class	Defect	Non-defect
Defect	889	162
Non-defect	52	200

Table 1: Class Mark List

$$Accuracy = \frac{\text{Correctly classified regions}}{\text{Total number of evaluated regions}} = 83.57\%$$

Results: Hit/Miss/Fail

Training 1 Training 2



Results: Hit/Miss/Fail

	ı							
Training			1				2	
Picture	Hit	Miss	Fail	% Defect Detection	Hit	Miss	Fail	% Defect Detection
Test 1	6	0	1	100.00	5	0	0	100.00
Test 21	6	1	2	85.71	5	1	0	83.33
Test 30	7	0	3	100.00	7	0	3	100.00
Test 41	10	2	0	83.33	10	2	0	83.33
Test 50	2	0	5	100.00	2	0	6	100.00
Test 59	5	0	1	100.00	5	0	0	100.00
Test 61	7	3	3	70.00	9	1	1	90.00
Test 70	7	0	3	100.00	8	0	2	100.00
Test 79	8	3	2	72.73	8	2	2	80.00
Test 91	4	0	3	100.00	4	0	2	100.00
Test 99	1	0	1	100.00	1	0	1	100.00
Test 108	4	1	5	80.00	3	1	1	75.00
Test 116	8	3	2	72.73	6	3	1	66.67
Test 125	5	4	3	55.56	8	2	2	80.00
Test 133	6	0	2	100.00	3	0	0	100.00
Test 139	9	0	1	100.00	10	0	0	100.00
Test 150	5	1	0	83.33	4	1	0	80.00
Test 160	1	0	1	100.00	1	0	0	100.00
Test 165	6	1	4	85.71	7	1	2	87.50
Test 190	5	1	3	83.33	6	0	0	100.00
TOTAL				84.85				88.89

Hit: Defect spotted

Miss: Defect not spotted

Fail: Bounding box on nothing

- Pros & Cons
- Pros
 - Robust through blur & lighting
 - Possibility to do continuous learning
 - Doesn't require any special setup*

- Cons
 - Need to build initial database
 - Needs a lot of pictures
 - Initial parameters need tuning
 - Training time and computer resources

Recommendations

To gain reliable results, we need to have :

A lot of pictures for the training
 Approach works by seeing different scenarios

To take pictures of all the parts/defects
 The algorithm is very good for what it trained for

Conclusions

- The proposed Faster R-CNN approach can detect defects and may be further improved to gain higher accuracy.
- It helps to improve the inspection process for the personal by showing them where possible defects are.

Acknowledgements

 Pratt & Whitney Canada is deeply thanked for its help and assistance through this project.

THANK YOU FOR YOUR ATTENTION!