Learning to Identify Drilling Defects in Turbine Blades with Single Stage Detectors

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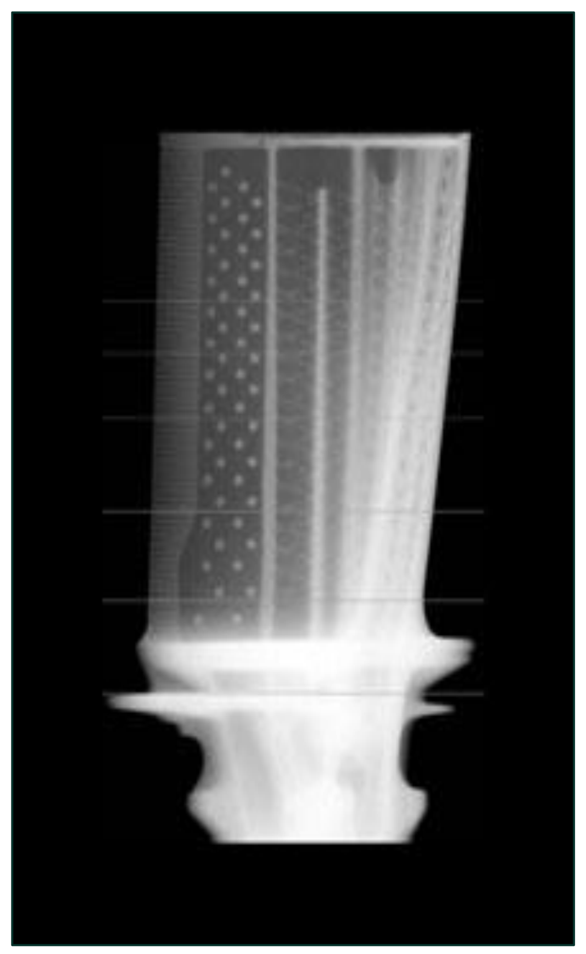
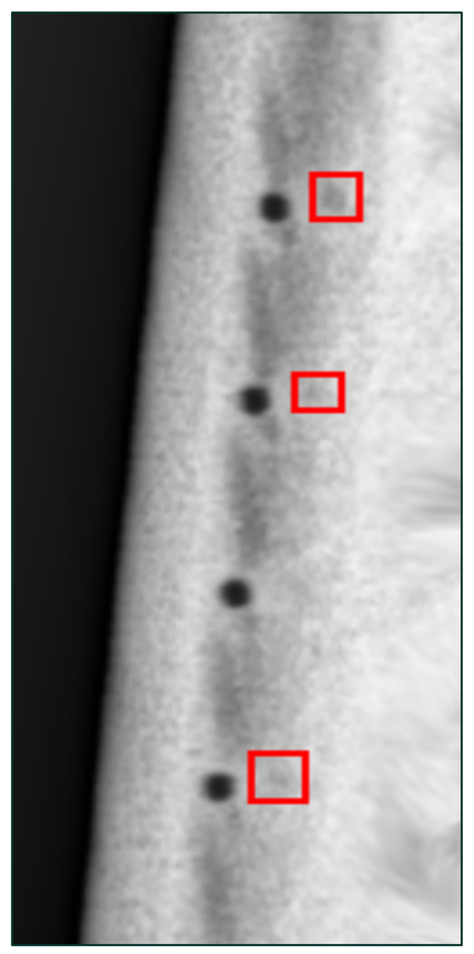
Motivation

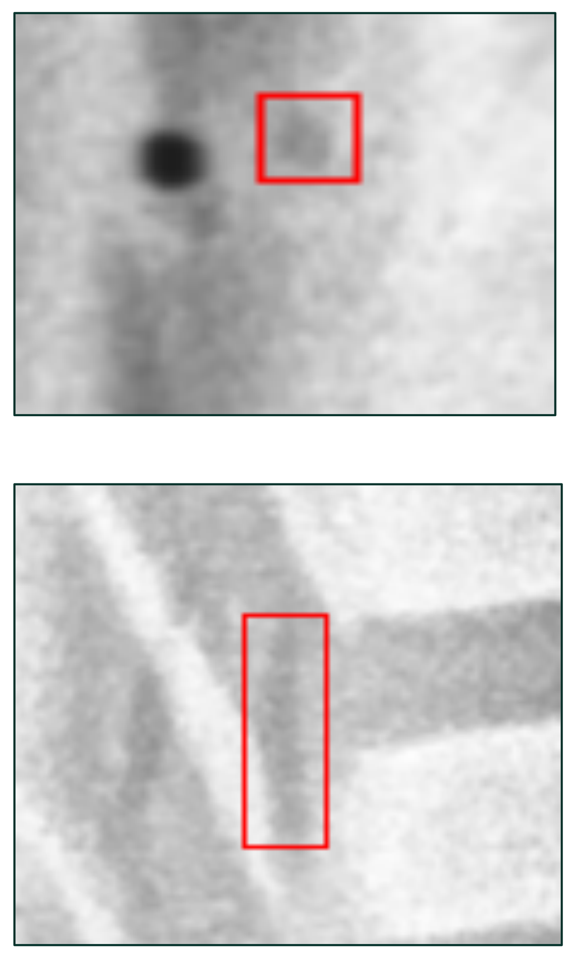
Defects in turbine blades can impact the operating life, safety and performance of the gas turbine, so they have to be detected before assembly[1]. To this end, we acquire X-ray scans of the blades from different viewing angles. Manual detection of drilling defects in these X-rays is tedious, time-consuming, and requires expert knowledge. Thus there is a significant opportunity to increase operating efficiency by automating the detection process with Machine Learning.



A turbine blade (not a BH one)

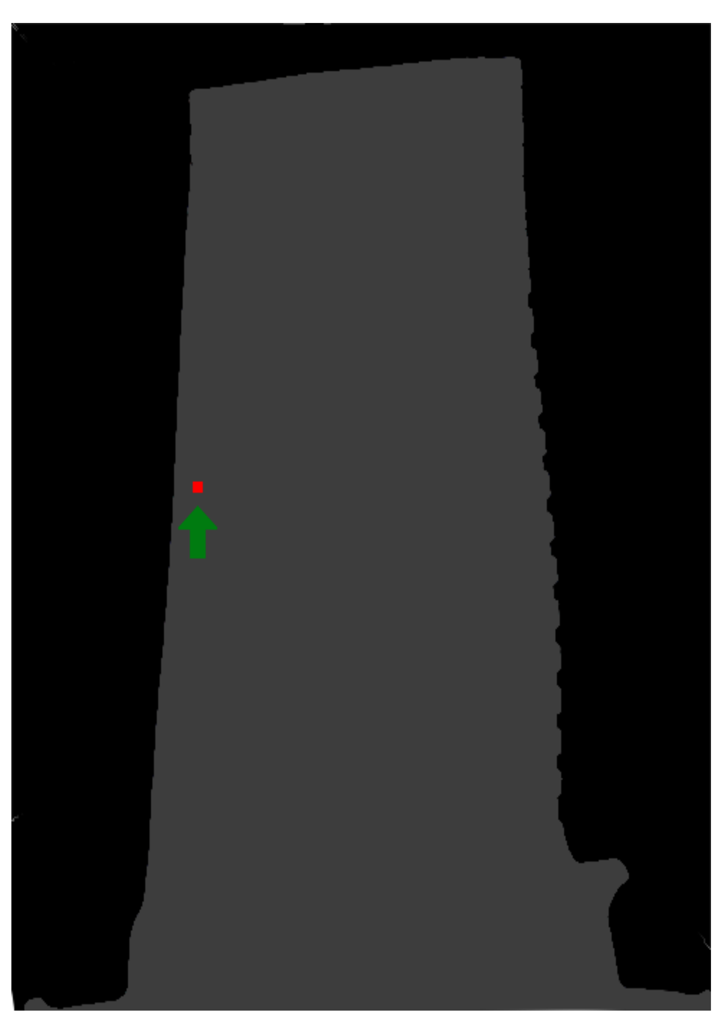


Examples of drilling defects



Defects and their close context

Main Issues



size of a blade vs. size of a single defect

Defects are hard to find

- Experts sometimes need to look at **multiple views of a blade** to identify a shape as a defect
- **Context matters**: a defect-like shape in the wrong place is not a defect

Small and Unbalanced Data Set

- 498 blades – **only 88 with defects**
- Multiple views (poses) for some blades
- 694 distinct poses – 134 with defects

Large Images

- 1500×1900 px

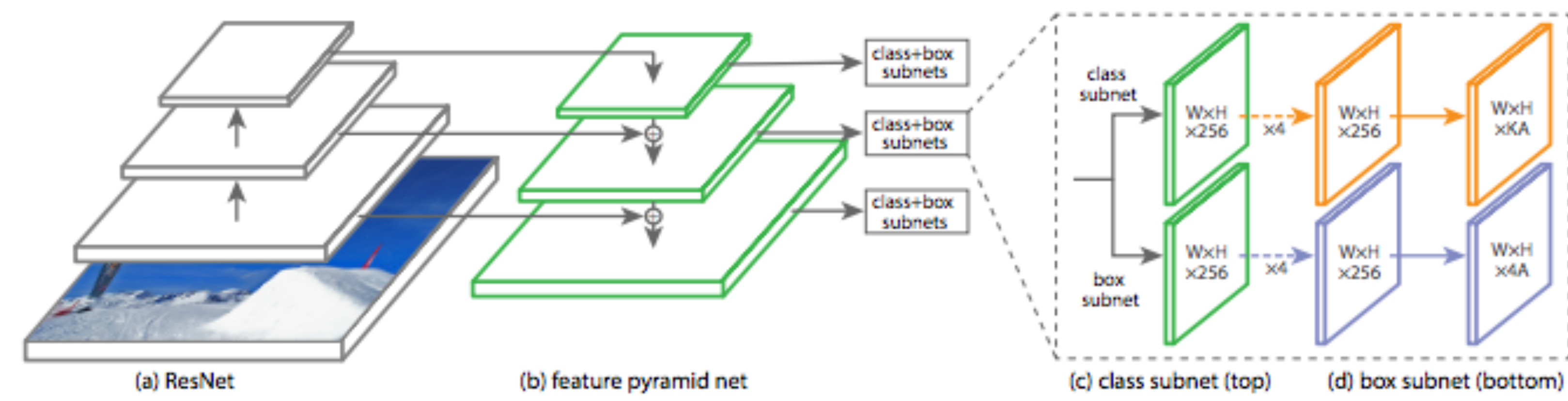
Small Defects

- Average defect dimensions: 14 x 20 px
- Large ratio between image and defect size

Detector Model

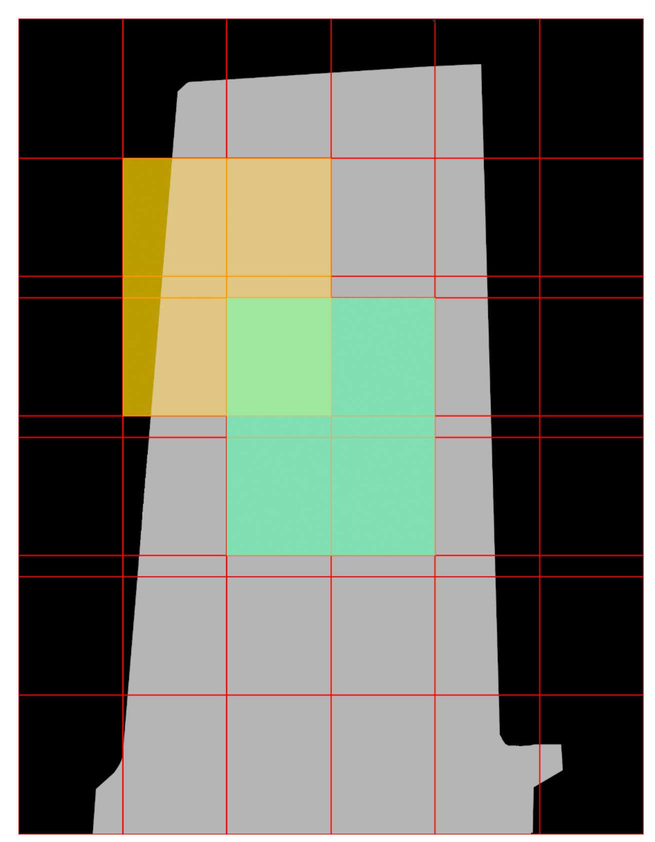
Retinanet [2]

- **Single stage detector** using **focal loss**
- **Anchor boxes** are assigned to ground-truth object boxes



a) **bottom-up pathway**, the backbone network which calculates the feature maps at different scales (ResNet-50)
b) **top-down pathway** and **lateral connections**
c) **classification subnetwork** predicts the probability of an object being present at each spatial location for each anchor box and object class
d) **regression subnetwork** regresses the offset for the bounding boxes from the anchor boxes to a nearby ground-truth object, if one exists.

Approach



Large Images / Small defect area

- 5×5 **overlapping tiles** of 500×600 px
- **Scale up tiles** by 2× in height and width

ratio between defect area and smallest anchor area increases

Unbalanced data set

- Extract a **balanced sub-set**

Small data set

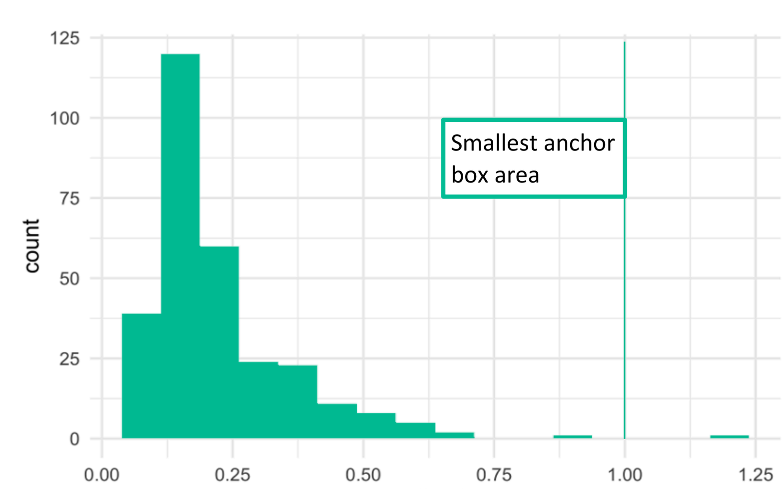
- Apply data augmentation

via random transforms

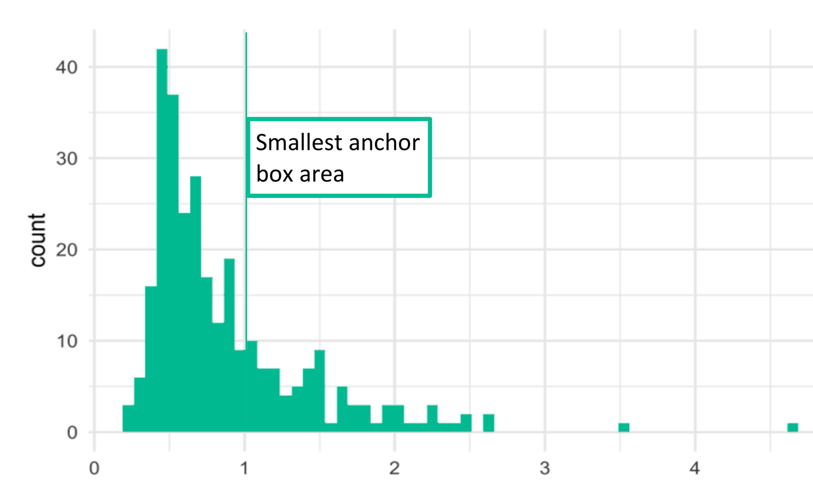
Improve performance

- Optimize anchor sizes and aspect ratios

with differential evolution search [3]



Area distribution of defects, normalized wrt area of smallest anchor box (32x32). Most of the defects are very small – below model thresholds



Distribution of normalized defects area after **upscaling 2x** – the distribution mean is much closer to 1

Results

Settings	mAP	Accuracy*
Original images (1500×1900), default RetinaNet parameters	0.06	0.56
Split tiles (500×600), default RetinaNet parameters	0.10	0.53
Split tiles + 2× upscaling (1000×1200) + random transform	0.73	0.90
Split tiles + 2× upscaling (1000×1200) + random transform + anchor optimization	**0.90**	**0.94**

*the accuracy is a custom metric, more aligned to our business goals, obtained by recasting the defect detection task as an image classification task (more details in paper)

Findings

- We developed a functioning model for identifying drilling defects in X-ray images of gas turbine blades.
- Training a vanilla RetinaNet model on our dataset did not deliver usable results.
- We identified the key issues:
  - large image sizes
  - small annotations area – (this turned out to be a key finding!)
  - small and unbalanced data set
  - use of default anchor scales and aspect ratios, not optimized for our data distribution.
- The final model delivers very good results

Future Work

- Deploy the model in production
- Apply the same methodology to Non-Destructive Testing of other gas turbine components

References

[1] J. Aust and D. Pons, “Taxonomy of gas turbine blade defects”. In: Aerospace , vol. 6, no. 5, p. 58, May 2019. http://dx.doi.org/10.3390/aerospace6050058

[2] Lin, T. Y., Goyal, P., Girshick, R., He, K., & Dollár, P. (2017). “Focal loss for dense object detection”. In Proceedings of the IEEE international conference on computer vision (pp. 2980-2988).

[3] M. Zlocha, Q. Dou, and B. Glocker, “Improving RetinaNet for CT Lesion Detection with Dense Masks from Weak RECIST Labels” http://arxiv.org/abs/1906.02283