Autonomous Crack Detection using Synthetic Thermogram Datasets

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Motivation

Failure due to Crack Propagation

- Local cracks can propagate and cause failure in different parts of the material

Corrosion

- Cracks make a material more susceptible to corrosion

Hence, early detection of cracks is important to ensure structural integrity

Problem Statement

Issues with Current Methods of Crack Detection

- Manual inspection is very time-consuming and also prone to human error
- It also requires skilled and experienced specialists

Can we build an automated system to efficiently identify cracks?

Challenges for Algorithm/Model Development

- These models *usually* need huge amounts of data for training
- Experimental data is extremely costly to obtain in terms of time, energy and money

Solution: **Fine-tuning on synthetic data!**

Recap

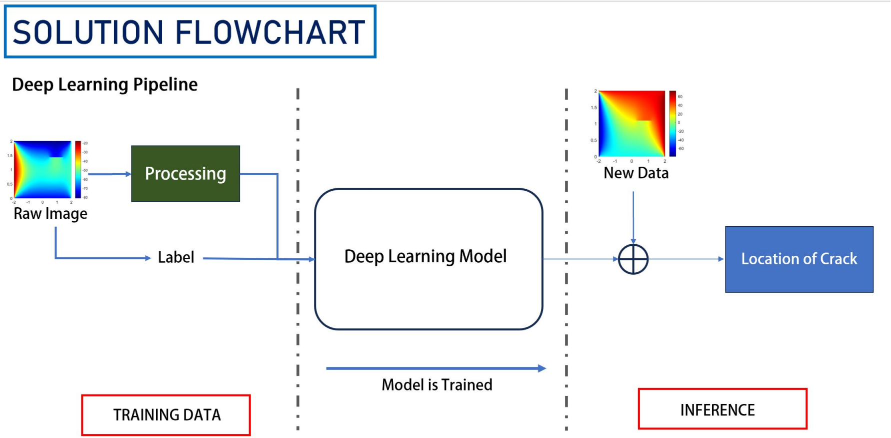

Figure: Eagle's eye view of the deep learning solution

Summary of work done in BTP-1

- Created a MATLAB finite element simulation pipeline for thermal profile generation
- Did a survey of current literature in the field and searched for existing datasets; which were generally hard to find
- Benchmarked the FEM simulations for a specific case with the analytical solution given in literature
- Explored image processing methods such as Otsu Thresholding, Hough Transforms, RANSAC and finally Convolution using Filters
- Trained a YOLOv5 Model on the synthesized dataset to perform bounding box detection

Dataset Improvement

Issues with earlier dataset

- In the earlier dataset creation code, only horizontal cracks were being defined
- Further, BCs were being applied only on the outer edges of the plate

Updating the data generation machinery

- Now, we have incorporated changes in the angle, width and length of the crack as well
- This adds randomness to the crack position and angle and hence is better
- Also, to increase variety, we are also applying heat flux and temperatures on the crack edge

Simulated Dataset

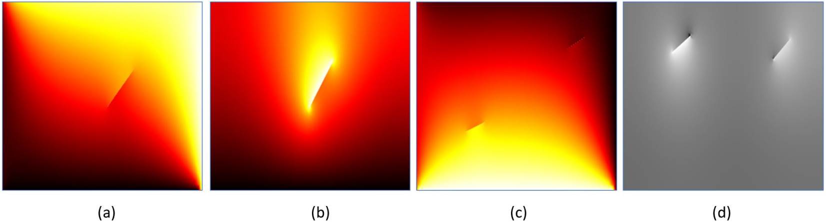

Figure: (a) Non-trivial BCs only on outer edges of plate. (b) Non-trivial BCs on edge of the crack in addition to plate edges. (c) More than one cracks on the plate. (d) Grayscale image

Segmentation v/s Detection

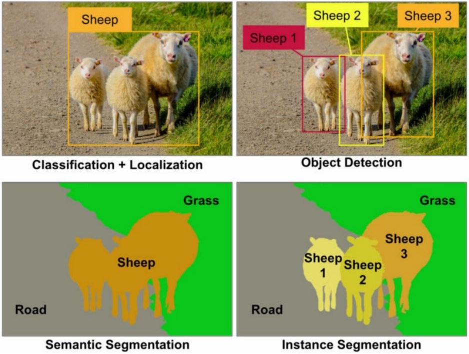

Figure: Image credits - Nirmala Murali - Medium

Out of these, the relevant ones for us are Object Detection and Instance Segmentation. YOLOv5 based Detection was performed earlier. This time, we performed Instance Segmentation using Detectron2.

Segmentation v/s Detection(2)

Category	Segmentation	Detection
Advantages	Precise object boundaries	Faster processing
	Useful for counting	Identifies objects
Disadvantages	Complex and computationally intensive	Not as precise

Table: Comparison between Segmentation and Detection

Annotation Process

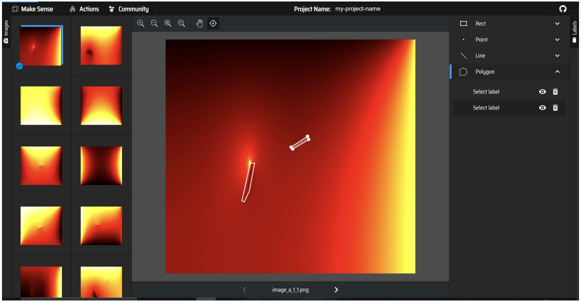

Figure: Annotation using Makesense.ai

- The annotation part involves drawing polygons around each crack in an image
- It is very hard to automate this part since untrained models cannot pinpoint on the crack location

Detectron2

- Detectron2 is a computer vision model zoo of its own written in PyTorch by the FAIR Facebook AI Research group.
- One can use Detectron2 to do key point detection, object detection, and semantic segmentation
- Out of the model zoo, we picked up a **Mask RCNN Model**

Mask RCNN

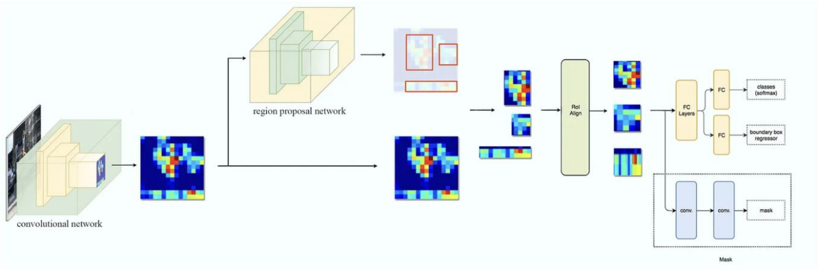

Figure: Mask RCNN Architecture. Image credits - Jonathan Hui

Mask RCNN (2)

- Mask RCNN detects objects and precisely segments them, further it has pixel-level segmentation capabilities.
- It combines object detection and instance segmentation tasks, providing detailed masks for each detected object instance.
- The architecture integrates a region proposal network to accurately localize objects in an image.
- Region proposal generates candidate bounding boxes where objects might be located based on features such as edges, textures, or colors.

Fine-Tuning

- To fine-tune a model, we choose a pre-trained deep learning model with relevant architecture and trained on a large dataset.
- We adapt the model our specific task by retraining it on your own dataset, adjusting original weights.
- This freezes initial layers which capture generic features like edges, while updating later layers for task-specific features.
- We fine-tuned the Mask RCNN model on the thermal profile dataset which we had generated

Training Dataset

- The number of images in each division was as follows: **Training = 105**, **Validation = 30**, **Testing = 15**

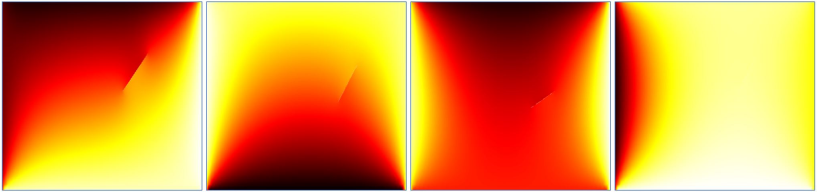

Figure: Images in increasing order of difficulty for a human annotator from left to right

Inference Results

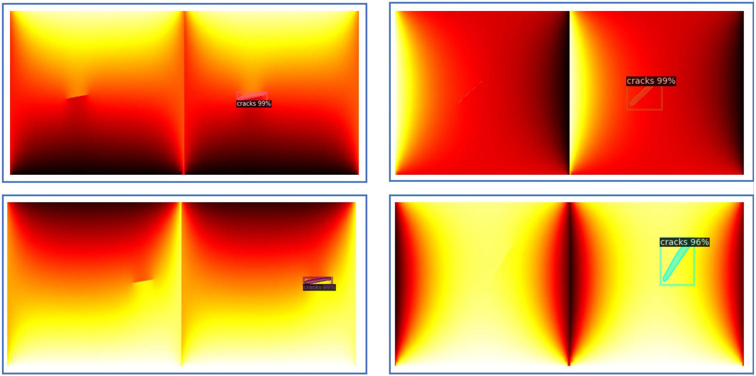

Figure: In each of the four examples, the model is accurately able to predict the location of the crack with very high confidence. This is a significant improvement. It even succeeds on the examples on the right which are quite hard for a human. **The model was able to correct predict the crack location in 15/15 examples!!!**

Conclusion

- Fine-tuning state-of-the-art Detection and Segmentation Models on synthetic is an effective way to build autonomous crack detection systems
- The model learned to make highly confident predictions with less data
- Personal Opinion: Application of ML to engineering applications is now a very **data-driven** objective. We have reached close to the peak in terms of models, what we now need is **diverse datasets** and **smart training methods**

Future Scope

- <u>Diverse Datasets</u>: From our experiments, we observed that Diversity $>$ Quantity!! We need to incorporate a variety of images; the size of the dataset is not much of an issue as the model is able to learn fast.
- <u>Domain Adaptation</u>: Can a model trained on dataset A achieve high accuracy on Dataset B?
- <u>Image Augmentation</u>: Can we use the data we already have to synthesize a greater variety of data? We have one idea for how to do this.
- <u>Sub-surface Cracks</u>: We have only looked at settings were the cracks are close to the surface. Can we make use of 3D data for sub-surface cracks?
- <u>Generation of complicated data</u>: Employ software with stronger simulation capabilities to generate more complex data and situations

Image Characteristics

- **Brightness**: The intensity of light in an image, affecting how light or dark it appears overall.
- **Exposure**: The amount of light that reaches the camera sensor, determining how light or dark an image appears.
- **Saturation**: The intensity or purity of colors in an image, influencing how vivid or dull they appear.
- **Contrast**: The difference in brightness between the lightest and darkest parts of an image, affecting its overall clarity and definition.
- **Warmth**: The presence of red and yellow tones in an image, influencing its perceived temperature or mood.

Manual Image Augmentation

We suggest a method to increase the dataset and also create examples which might be harder for the model to detect. This will improve **robustness** of the model

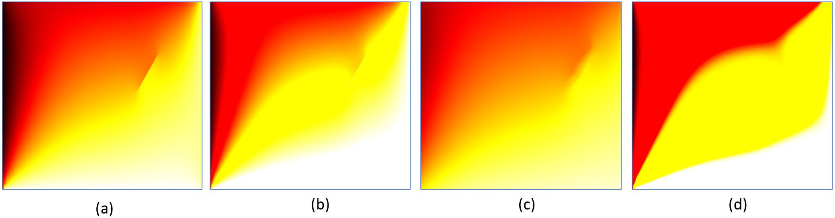

Figure: From left to right $\longrightarrow$ (a) Original image. (b) Image with high Brightness. (c) Image with parts near the crack blurred to decrease visibility. (d) Image with contrast, brightness and exposure adjusted such that it is harder to locate the crack

References

- Yang, Wang et al. “Infrared Thermal Imaging-Based Crack Detection Using Deep Learning (2019)”
- Jaeger, Schmid et al. “Infrared Thermal Imaging-Based Turbine Blade Crack Classification Using Deep Learning (2022)”
- https://github.com/facebookresearch/detectron2
- https://www.youtube.com/c/DigitalSreeni

Thank You!