Autonomous Inspection and Reliability of Renewable Energy Assets

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Abstract

Today, countries have enabled climate change mitigations by investing in renewable energy assets, such as wind turbines. While wind energy and wind turbines have a series of benefits, one aspect that limits their expansion is their operation & maintenance costs. While these costs have been a limiting factor, the most promising method to reduce these costs is a deep learning-based approach. The aim of this research was to develop a fully autonomous deep learning-based approach that can accurately classify the type of damage on a wind turbine. The deep learning model was trained using a YOLOv4 model, a deep learning object detection framework, which was tested on real world drone inspection data. This approach was able to achieve 90.00% accuracy in detecting damages, which was found to be 22.22% better than an existing deep learning benchmark model.

Background

- For operations to inspect wind turbines, which sit 262 feet high is incredibly risky. Not to mention to inspect the blades which are 120 feet long is labor intensive.
- Offshore wind farms are even more difficult to access and thus operation & maintenance of offshore wind farms tends to be higher than on shore wind farms.
- Operation & maintenance of offshore wind turbines make up to 25–30% of the total costs sustaining an offshore wind farm.
- Currently, drone inspections can cover up to 10 or 12 turbines daily, reviewing each blade within anything from four to nine minutes. This compares to a manual inspection rate of two to five turbines a day [7].
- Drones can deliver clear, precise imagery of the entire blade, with up to 40 mega pixels for ultra-high resolution. When using technologies like LiDAR, you can also get detailed measurements of any defects. These images can then be analyzed to provide actionable inspection results. [6]

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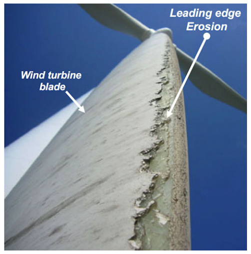
Methods and Materials

Download DTU Drone Inspection Data Set → Upload Data into Roboflow & Apply Pre-processing Steps → Apply Augmentation to Images & Split Data into Train-validation Test → Upload Images to Google Collaboratory & Train Proposed YOLOv4 model → Run YOLOv4l & Evaluate Predictions



Leading edge erosion is often caused by raindrops, hailstones or other particles impacting the leading edge of the blade. In turn, this causes the material to be removed off the surface of the blade, leaving a rough profile that degrades the performance of the blade over time.

Since the dataset had a limited number of images, some damage types had less representation. However, the deep learning model requires many images to train a model that can recognize the distinctive damage feature so that it can detect the correct damage on the testing images. Therefore, using Roboflow, the images went through augmentations, such as a horizontal flip, 90-degree rotation, crop, shear, saturation, and brightness. Along with augmenting the image, the bounding box annotations were also augmented with the same augmentation steps.

In terms of the deep learning model, the model used for this research is a YOLOv4 model. YOLOv4's architecture comprises of a CSPDarknet53 backbone, spatial pyramid pooling additional module, PANet path-aggregation neck, and YOLOv3 head. The spatial pyramid pooling block is added over CSPDarknet53 to increase the receptive field and separate out the most significant context features. The PANet is used as the method for parameter aggregation for different detector levels [5]. The process by which CNN learns about the features is during the training process. A CNN contains multiple layers, where the information is passed from one layer to the next. When the image reaches the final layer, a feature map is created for that image.

Results

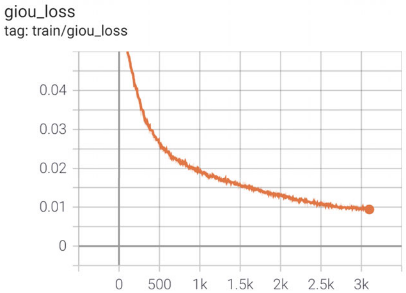


Figure 3: GIoU Loss Function

Figure 4: YOLOv4 Model output

Table 1: Comparison of Results

Bold-Faced Values Indicate Best Performance

	mAP		Accuracy	
	No Damage	LE Erosion	No Damage	LE Erosion
YOLOv4	**88.32%**	**84.13%**	**90%**	
YOLOv4 Benchmark	45.28%	34.87%	70%	
Faster R-CNN	37.05%	26.62%	50%	

Future Direction

- As research into deep learning application with drone inspection of wind turbines increases, we hope to see more data available. As more data is available, the more represented the damage types are. With increased representation, the better the model will perform because there is more data to learn from.
- Regarding detecting damage, as drones are becoming equipped with advanced sensors, like infrared cameras, they can collect various types of data. Thus, research can be done into developing a deep learning model that can take in multiple different types of data and make a prediction that is more precise regarding the type, severity, and location of the damage.
- In addition, as drone-based inspection is adopted to inspect wind turbines, there is room to research the implications of adapting drone-based inspection to solar farms.

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