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Research paper

Image based surface damage detection of renewable energy installations using a unified deep learning approach

ASM Shihavuddin [a], Mohammad Rifat Ahmmad Rashid [b], Md Hasan Maruf [a], Muhammad Abul Hasan [b], Mohammad Asif ul Haq [a,*], Ratil H. Ashique [a], Ahmed Al Mansur [a]

[a] EEE Department, Green University of Bangladesh, 220/D, Begum Rokeya Sarani, Dhaka 1207, Bangladesh
[b] CSE Department, University of Liberal Arts Bangladesh, House 56, Rd 4/A Satmasjid Road Dhanmondi, Dhaka 1209, Bangladesh

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ABSTRACT

Smart Grid technology as a platform can encompass several advanced technological features across the spectrum of the power system. Smart Grid may introduce an early warning system for structural damage on the surface of large-scale power utility facilities providing crucial information to maintain the safety of the plant. To achieve such a cost-effective structural health monitoring system, a holistic smart inspection implementation framework is required. Using recently available sophisticated inspection technologies, high-resolution images covering the structural condition of large infrastructure can be routinely acquired as a remote monitoring process. Automated analysis of these inspection images can significantly reduce the inspection cost, provide an effective detection mechanism, and shorten reporting time, as a result, reducing overall maintenance costs, and improving safety measures. In this work, we have applied state of art deep learning based inspection image analysis methods for surface damage detection of various renewable energy power plants with a single unified model. We have achieved the state-of-the-art accuracy of 0.79 mean average precision on average even where input images are of varied modalities: from thermal images to visual images, from high- to low-resolution images, and from PV panels to wind turbines. All variations have been tackled with one single deep learning model to detect surface damages. Our results demonstrate the promise of effectively deploying a single trained model to inspect a wide range of energy installations while reducing the monitoring cost significantly. In addition, this work also published the reported dataset comprising four specific image sets for the research community.

1. Introduction

The ongoing policy level and public demand for rapid transition of energy dependencies to be moved from fossil fuel to renewable zero-carbon energy sources encourage the developing nations to take proactive actions in this regard. Governments of developing countries are in urgent need to take well-planned measures in energy management to achieve sustainable economic and social growth, environmental safety, and nature conservancy (Amin and Wollenberg, 2005; Garrity, 2008). However, often the importance of monitoring and maintaining the health conditions of the power plants are either ignored or downplayed in those policies risking the sustainability of related investments and national energy security (Acharjee, 2013; Maruf et al., 2020).

Effective Energy management is one of the main transformations required to attain sustainable development goals set by the United Nations (UN). Hydro, wind, solar and nuclear energies are among the largest non-conventional sources of electricity generation. Among them, wind and solar are to be the key factors contributing to the achievement of sustainable development of countries all over the world according to the International Energy Agency (IEA). For cost-saving, all countries are now investing heavily in very large installations of these renewable power sources. Such installations require sophisticated maintenance and monitoring systems mainly on the structural and surface part to continue generating the expected amount of energy on regular basis. Compared to available inspection methods, image-based monitoring could be one of the most promising solutions because of its effectiveness and as well as low-cost mechanism. In

* Correspondence to: EEE Department, Green University of Bangladesh (GUB), 220/D, Begum Rokeya Sarani, Dhaka 1207, Bangladesh.
E-mail addresses: shihav@eee.green.edu.bd (ASM Shihavuddin), rifat.ahmed@ulab.edu.bd (M.R.A. Rashid), maruf@eee.green.edu.bd (M.H. Maruf), muhammad.hasan@ulab.edu.bd (M.A. Hasan), asiful@eee.green.edu.bd (M.A.u. Haq), ratil@eee.green.edu.bd (R.H. Ashique), mansur@eee.green.edu.bd (A.A. Mansur).

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drone image-based monitoring, large-scale renewable plants can be regularly monitored based on acquired data and the corresponding analysis to make the right decisions on maintenance ensuring the uninterrupted energy supply. Wind and solar are the most popular forms of renewable energy over the years due to rapid technological advancements and continuous reduction in production costs (Lund, 2007). Countries around the world are pushing hard with necessary policy adaption to increase their power generation capacity from these two sources (Lund and Mathiesen, 2009; Lindenberg, 2009). In our work, we also focused mainly on the damage monitoring of these two types of energy installation. Wind and Solar can be deployed on large scale or in a micro grid depending on the need and financial arrangements. Automated decision-making and Artificial Intelligence (AI) based monitoring could be the way forward for such technologies towards achieving Industrial Revolution 5.0. Drone-based solutions and systems are mainly designed as referred in this work for large-scale installations. A large-scale wind turbine may consist of wind turbines 70 meters in height, whereas a large PV plant may cover around 50 acres of land area.

Wind turbines are frequently installed in remote locations and often exposed to severe weather conditions (Ribrant and Bertling, 2007). The rotor blades, as one of the most important components in the wind turbine system, are responsible for converting mechanical energy from the wind to electricity. During the expected design life of 20 to 25 years of operation, wind turbine blades are subjected to significant fatigue loads, which degrade the structural and aerodynamic performance, sometimes even leading to expensive fatal structural failure. These types of degradation incur considerable repair costs and the downtime of power generation. Besides being caused by the fatigue loads, these types of damages can also arise due to manufacturing defects, external weather conditions, operational errors, and so forth (Shohag et al., 2017). For PV panels, the impact of weather also has a significant impact. Their performance may also degrade due to aging and power mismatch (Al Mansur et al., 2019; Mansur et al., 2019). Fig. 1 illustrates visually detectable damage traits on both wind turbine blades and PV panels. These damage traits in both cases are visually different but spatially consistent, which means that due to camera position, the images can have some affine transformation in the perspective of the objects of interest in the images, but the structural geometry remains consistent. This makes it possible for machine learning models to characterize and detect damages during inference on test images.

Detecting these types of damages with drone images requires an efficient and automated image processing method. Automation can decrease the required processing time and minimize human involvement to reduce expert hour costs. Thorough experimentation by training deep learning based models can evaluate the effectiveness of such a system. Having one single model for mentioned cases overcomes the challenges of training machine learning models on each separate modality incurring computational and data collection overloads. Also, a model when learned within large variation becomes more robust and unified as shown in the results with later sections. In the earlier work on deep learning based damage detection (Shihavuddin et al., 2019), the authors measured human accuracy in terms of Mean Average Precision (MAP) on the wind turbine dataset which is among the dataset used in this work as well. There the human level MAP reported was around 84%, and with the help of the automated damage detection tool as a suggestion box it went up to 87% which was higher than any other standalone Machine Learning (ML) model. In that regard, reaching around 86.6% with a single network i.e., YOLOv5 on the wind turbine data set is better than the average human precision, and almost as good as the precision of human aided with suggestion systems.

Extracting damage information from a large number of high-resolution inspection images requires a significant manual effort. Therefore, the overall maintenance cost remains at a high level due to the considerable manual image revision cost. Manual image inspection is also tedious and therefore error-prone. By automating the detection of damages from drone inspection images, or at least by automatically providing suggestions to experts on highly probable damage locations, we can significantly reduce the required expert hours and as a result, minimizing the cost involved in analyzing the inspection data. At the same time, automated analysis and a suggestion system for human annotation increase the accuracy of the damage detection as reported by Shihavuddin et al. (2019). Automating the detection from acquired drone images is challenged by:

- ➢ Size and scale variations: Surface damages on power installations may come in large variations of size and shape. Moreover, due to drone distances from the object of interest and perspective angles variation, the sizes and shapes of even the similar damage types may present large variations in their visual representation.
- ➢ Light conditions: Luminance and shadows in inspection images depend on the time of the day and the weather conditions during inspections. Variations in light conditions lead to variations in color, brightness, saturation, and contrast in the acquired images.
- ➢ Rare damage types: Some types of damages are rare, and it can be difficult to acquire enough representative samples. This issue is particularly problematic for machine learning methods. Deep learning based solutions, as we employ here, typically require a hundred to a thousand examples.

In this particular work, we addressed the above-mentioned challenges extensively with the help of advanced deep learning frameworks. In recent years, Convolutional Neural Network (CNN) based deep learning for object detection framework has regularly produced groundbreaking performances. Our proposed method was tested on wind turbine blades, PV panels, demonstrating the promise of the extensibility to other large power plant maintenance. Fig. 2 illustrates the proposed framework for using drone-based detection and analysis for predictive maintenance of power installations having a machine learning backbone using deep learning. The proposed framework is segmented into three major components where the first part deals with image acquisition using deference sensor modalities with drones, the second part handles the machine learning to learn about damages, and in the application is applies the learning to infer the location of damages, estimate the severity based on the location and suggests possible to measures to the human decision-maker.

The main contributions of this work are as follows:

- ✓ Deployment and comparative study on the performance of EfficentDet-D0 to EfficentDet-D5 and YOLOv3 to YOLOv5 for the first time in the application of the damage detection from the drone inspection images of Wind turbine and PV Panels.
- ✓ Use of a single trained model for detection comprising training sets from Infrared and optical drone inspection images of Wind turbine and PV Panel surface damages with a wide spectrum of resolutions ranging from 100 × 100 pixels to 3264 × 1836 pixels and resulting in relatively higher accuracy.
- ✓ Demonstrating that enhanced generalizability of the trained models is achievable by harnessing surface damage examples from varied backgrounds and thereby avoiding overfitting and reducing training costs.

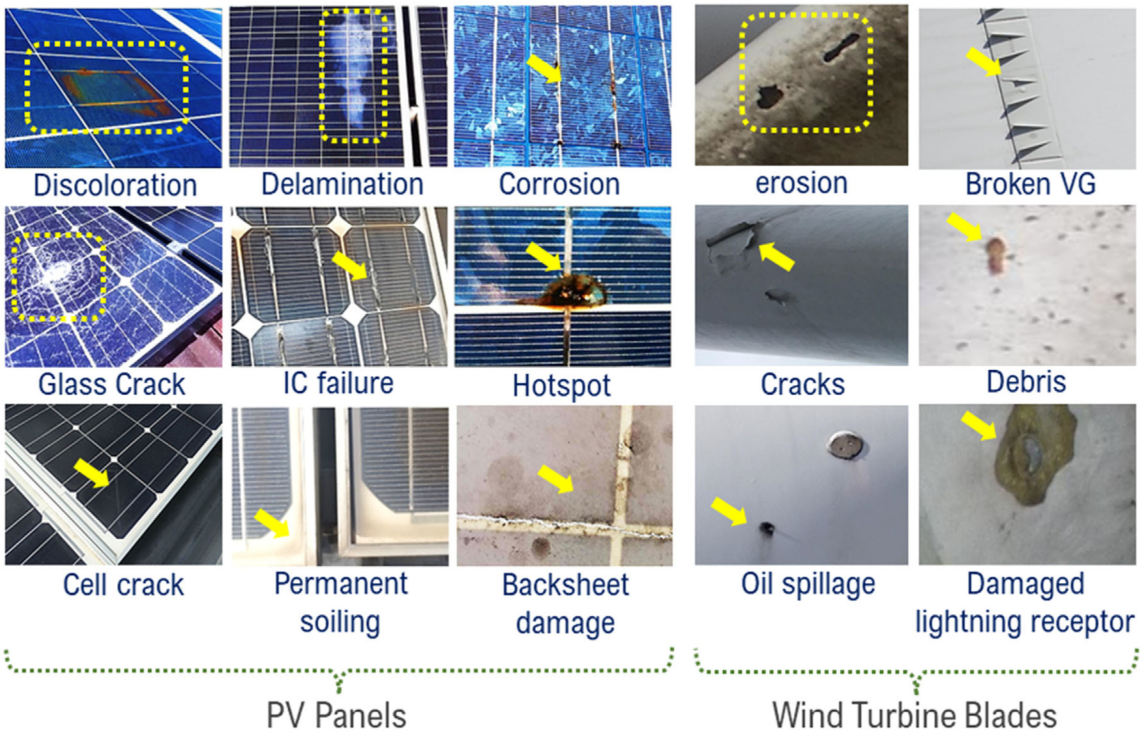

Fig. 1. Examples of surface damages on solar panels and Wind Turbine Blades. VG stands for Vortex Generator.

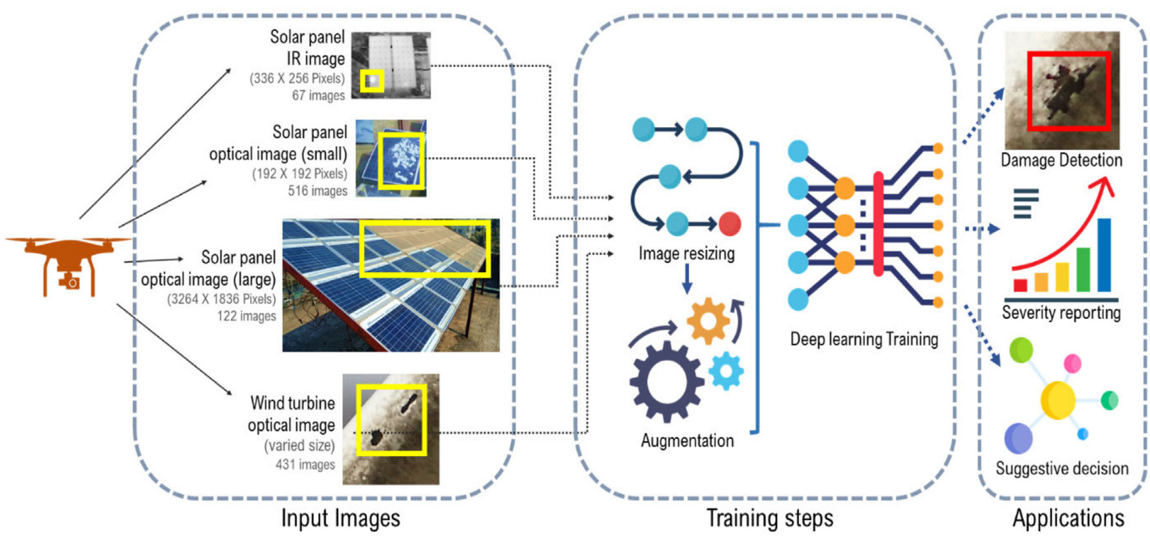

Fig. 2. Example of the proposed framework for surface damage detection and smart monitoring of power installations.

✓ Publication of a brand new dataset for the research community comprising expert annotated damages on Wind Turbine Optical Images, Solar Panel Optical Images (Small), Solar Panel Optical Images (Large), and Solar Panel Infrared Images.

2. Related work

Researchers over the years developed solutions to routinely monitor the health conditions of varied power plants for early damage detection (Artigao et al., 2018), though these solutions were power plan type-specific. To the best of our knowledge, no general monitoring method across all varied types of power plants has been extensively explored before the presented work. In general, these monitoring methods involve various types of sensors that are discussed in these review works Márquez et al. (2012), Hameed et al. (2009), Ciang et al. (2008), Rumsey and Paquette (2008) and Martinez-Luengo et al. (2016). Some of the major works in health monitoring technology include vibration sensors (Ozbek et al., 2013), acoustic emission sensors (Anastassopoulos et al., 2003), strain sensors (Schroeder et al., 2006), and ultrasound sensors (Raišutis et al., 2008). These methods designed for specific damage types are mainly expensive, regular replacement of sensor devices and related hardware is required, and also in most of the cases, the results are limited to laboratory testing.

With recent advances, drone-based inspections provide a good alternative solution as they can provide non-contact and remote visual inspection in a short time (Shihavuddin et al., 2019; Zhang et al., 2020). Drone inspections are currently being successfully used for other structural health monitoring of infrastructure, like bridges, towers, power plants, and dams (Morgenthal and Hallermann, 2014). These types of drone-based solutions are extendable to large power installations adopting the automated training system to case-specific damage types. Surfaces of large structural installations contain recognizable visual traits of potential damages that can be imaged by drones with optical cameras. These damages are nowadays still captured using error-prone and expensive manual labor with the risk of causing health hazards.

Commercially, there have been many applications that are becoming popular for visual inspection and monitoring of varied large infrastructure. Drone inspection that can even be fully automated is slowly replacing the current human drive monitoring process. In remote-controlled drone inspection, expert personnel performs overall mission planning and execution taking the help of GPS data. The inspection data in terms of images and GPS locations could be further analyzed for decision making on the appropriate procedures regarding follow-up maintenance. Regular inspections of large infrastructure can significantly improve the early identification process of surface damages and reduce maintenance costs as well as the risk factor and energy loss. As per previous studies, a significant amount of operational and maintenance cost per Megawatt (MW) could be saved using drone-based inspection and monitoring, however, the amount depends on the cost of equipment, location, and many other factors. Unmanned aerial vehicle (UAV) or drone-based inspection had also been previously successfully used incorporating different types of sensors for varied categories of infrastructure and natural disaster monitoring (Entrop and Vasenev, 2017; Rakha and Gorodetsky, 2018; Shihavuddin et al., 2013). For example, Yu et al. (2018) used satellite images to map and monitor installations of PV panels all over the United States using a machine learning framework.

The main advantages of drones can be summarized as

- ➢ Low-cost solution with less health hazard and expensive expert man-hour involvement minimized.
- ➢ Faster and automated reporting on the surface condition and severity mapping regarding the site of interest
- ➢ Higher quality visual sensor data acquisition compared to satellite data is possible, based on the sensor type mounted on the drone. Moreover, with multiple sensor types, the multi-spectral acquisition could be enabled and with sophisticated Global Positioning System (GPS) technology accurate location could be mapped
- ➢ Inaccessible areas can be covered with drones even in harsher conditions.

Solar panel (PV) inspection with drones (dos Reis Benatto et al., 2017; Alfaro-Mejía et al., 2019) using either or both optical and thermal cameras had also been explored in other works. These works in general follow the first step acquisition from sensors and the second step as concurrent analysis using computer vision algorithms (Zefri et al., 2018). Aghaei et al. (2015, 2016), Dotenco et al. (2016), and Yap et al. (2015) used a classical image processing approach for detecting damages on infrared camera images. Deep learning based drone inspection image analysis for PV was first proposed by Chen et al. (2018) and Mehta et al. (2018), where adaptation of conventional neural network was applied to better performance on multi-spectral images detection and interpretation. Fig. 1 illustrates different damage types such as soil, dust, and cracks on PV panels (Kumar et al., 2018; Lee and Park, 2019; Grimaccia et al., 2015; Teubner et al., 2017; Mehta et al., 2018) and leading-edge erosion, cracks, holes, burned portion, damaged portions, etc. on the Wind Turbine Blades.

Drone-based inspection applies to other large power stations as well. For example, in one large thermal power plant, the chimney might get damage due to lightning strikes during thunderstorms exposing the internal structure. At the same time, large infrastructures can easily start forming erosion, creaks due to external factors, and faulty production during installations. Very few research works have addressed automated methods for surface damage detection of the power plants like wind turbines (Wang and Zhang, 2017; Shihavuddin et al., 2019). Wang and Zhang (2017) used drone inspection images for crack detection. Shihavuddin et al. (2019) used drone-based inspection using the deep learning based analysis to detect damages on wind turbine blades with promising results. Automated detection of the damages using a deep learning based approach can reduce the manual labor involved. However, this approach is very much data-hungry and requires lots of annotated data to train form. The initial cost of deep learning training is a little bit higher, as for good accuracy, a substantial amount of training data is needed. Though once trained, the model can be reused for a long and eventually cut down the cost significantly. In many cases, such training data are already available in abundance.

Surface damage detection and classification on drone inspection images can be performed using faster R-CNN (Ren et al., 2015) which used to be the deep learning object detection framework in 2018. Inception-Resnet-V2 (Szegedy et al., 2017), a combination of Inception and ResNet modules, is one of the best CNN backbone architects to deal with large images. However, for our experimentation, we deployed the current state-of-the-art object detection methods mainly EfficientDet (Tan et al., 2020) and YOLO (Redmon et al., 2016).

To improve accuracy and efficiency, Tan et al. (2020) performed a systematical study of network architecture design choices for efficient object detection, and they proposed a weighted bidirectional feature network and a customized compound scaling method. Based on the proposed optimizations method, the authors develop a new family of detectors, named EfficientDet. In particular, the proposed scaled EfficientDet achieves state-of-the-art accuracy with much fewer parameters and the number of Floating-Point Operations Per Second (FLOPs) (which is often reported to represent the complexity of the computational resource requirement of an algorithm) than previous object detection and semantic segmentation models (Tan et al., 2020).

Considering the object detection accuracy in real-time, "You only Look Once" (YOLO) has been one of the key object detection research. YOLO utilizes only convolutional layers which makes it a fully convolutional network (FCN). Over a while, there are multiple versions of YOLO models are realized. In this work, we explore YOLOv3, YOLOv4, and YOLOv5 for wind damage detection. YOLO architecture consists of three main pieces.

- ➢ Backbone: A convolution neural network (CNN).
- ➢ Neck: multiple layers to combine image features to pass them forward to prediction.
- ➢ Head: obtain features from neck and perform bounding box and class prediction steps.

In YOLOv3 (Redmon and Farhadi, 2018), the authors presented a deeper architecture of a feature extractor (Neck) which contains 53 convolutional layers and it is called Darknet-53. In this architecture, each layer followed a batch normalization layer and Leaky ReLU activation. Furthermore, the authors did not utilize any form of pooling, and a convolutional layer with stride 2 is used to down sample the feature maps. This results in preserving the loss of low-level features attributed to pooling.

YOLOv4 (Bochkovskiy et al., 2020) approach explore the influence of state of art BoF (bag of freebies) (Zhang et al., 2019) and various BoS (bag of specials) (Bochkovskiy et al., 2020). Considering accuracy, BoF improves the accuracy of the detector taking into account less inference time. However, it only increases the training cost. The BoS significantly boost the accuracy of object detection however they increase the inference cost by a small amount.

After the release of YOLOv4, within two months, another version of YOLO has been released by Gleen Jocher which is called YOLOv5 (Jocher et al., 2020). It is different from all other releases of YOLO approaches, as this is a PyTorch implementation rather than a fork from the original implementation using Darknet Architecture. The YOLOv5 architecture uses CSPNet as the backbone (Wang et al., 2019) and PA-NET neck (Liu et al., 2018) similar to YOLOv4 architecture. The key improvements include mosaic data augmentation and anchors using an auto-learning bounding box.

3. Experimentation

With drones, it is possible to acquire numerous high-resolution images of a wind turbine of any other large power installation like solar, hydro, thermal, nuclear, etc. and use them to detect damages as leading-edge erosion, cracks, lighting receptor damage, missing teeth in vortex generators, missing structure materials, and so forth. For each type of power plant, the inspection criteria, conditions, and considerations could be widely varying. However, the output of those inspections is high-resolution images that can be used in the processing pipeline for automated damage detection and location identification. In Nuclear power plants, for example, regular inspections by the responsible section can be made for the reactor's exterior for early detection of formation probability of any kind of cracks, which may cause a catastrophic disaster in the future. Recent advances in machine learning coupled with extensive computational power have made it possible to train classification models for accurate object recognition. Recently, the deep learning methods known as convolutional neural networks (CNN) coupled with detection frameworks are providing state-of-the-art performances in object detection and classification (Krizhevsky et al., 2012).

In this work, as a case study, we applied deep learning for damage detection in the wind turbine and Solar Panel inspection images. We deployed the state-of-the-art deep learning object detection framework with a selected CNN to identify surface damages on blades. The experimental results show that CNN features make it possible to identify various damage types of interest regarding the surface of wind turbine blades. Moreover, this automated detection of the damage types can also be used as a suggestion system for manual annotation, thus reducing the required expert time.

The overall solution would have drones perform inspection remotely and send data to clouds for online or offline consecutive processing for damage detection. Based on damage types and their severity, a set policy would be triggered to solve the issues detected based on cost model analysis which is not part of the scope of this work. In this work, we explored the backbone damage detection system from images and proposed a sophisticated augmentation method to overcome the scarcity of trainable datasets.

3.1. Augmentation

Damages on large structures are scarce and are hard to collect representative samples of during inspections. For deep learning, it is necessary to have thousands of training samples that are representative of the depicted patterns to obtain a good prediction model (Perez and Wang, 2017). The general approach is to use example images from the training set and change their appearance such that they represent more of a variation in the appearance of the objects that should be recognized. For any augmentation types, it is necessary to maintain the consistency of the core properties of the classes.

Augmentation can be applied during both training and testing. During training, each augmented image is considered as individual input to the CNN network. In this work, we limited the scope to augmentation only on the training image sets. We then test our method on a dedicated test set of images. In this work, brightness, contrast, hue, saturation, horizontal flip, and vertical flip augmentation are used in the training over individual images.

3.2. Dataset

We have used 4 different datasets and their combinations to experiment with the state-of-the-art object detection frameworks backed by deep learning. We have used 80% of the dataset for testing, 20% for validation, and varied drone inspections images for testing. We have generated the Solar Panel Optical Images (Large) dataset with DJI Mavic Pro drone, posing the UAV two meters above the ground, capturing rooftop installations of PV panels for off-grid power supply to households, and the other three main datasets are taken from research works of others, accordingly referred to in the manuscript. Among them, Wind Turbine Optical Images were acquired by professional drone operators with sophisticated drones in DTU wind energy facilities in Denmark. Due to confidentiality issues, more information is not provided in that paper. Solar Panel Optical Images (Small) dataset was produced by Mehta et al. (2018) but the information of the image acquisition is not provided there. However, images of a similar kind can be easily acquired with drones. Solar Panel Infrared Images dataset was produced by Alfaro-Mejía et al. 2019 and annotated according to the snail trails and hot spot failures. They used a Zenmuse XT IR camera with a DJI Matrice 100 drone. All the images in this dataset are 336 × 256 pixels in dimension and grayscale. In a suitable weather condition for UAV inspection, the drone is positioned 2 meters above the panels (lower side) and covers twice the area of a panel cell capturing required details. For our experiments, there was a mix of these four main datasets to evaluate the performance of recent deep learning based object detection models for damage detections across non-uniform origins and image sensing modalities.

The dataset (Shihavuddin et al., 2020) is composed of images with annotation from mainly wind turbine optical images, PV panel close-up optical images, PV panel close-up infrared images, and PV panel long shot optical images. These image sets are described in detail below, summarized in Table 1 mentioning key properties of each dataset, and Fig. 3 illustrates 3 examples from each category.

3.2.1. Wind turbine optical images

This image-set was created from the drone inspection with optical cameras covering wind turbine blades from different installations in Wind energy firms across Denmark. These 431 images are of different resolutions ranging from 100 × 100 pixels to 1844 × 1281 pixels. These images mainly cover sample images of different types of surface damages on the wind turbine blades such as erosion, cracks, oil leakage, damaged lightning receptors, etc.

3.2.2. Solar panel optical images (small)

These 516 images are taken from the experiments performed by Solar Eye monitoring the effects of the soiling (having different particle sizes and colors) on power production regarding a control PV panel without soiling (Mehta et al., 2018). Here the images are 192 × 192 pixels in resolution.

Table 1
Detailed features of the image sets used in the dataset for the experimentation purpose.

Image set	Image type	Captured object	Acquisition by	Resolution	Color	N	Ref.
Wind turbine optical images	Optical	Wind turbine	Drone	100 × 100–1844 × 1281	Yes	431	Shihavuddin et al. (2019)
Solar panel optical images (small)	Optical	PV panel	Drone	192 × 192	Yes	516	Mehta et al. (2018).
Solar panel optical images (large)	Optical	PV panel	Drone	3264 × 1836	Yes	122	Ours
Solar panel infrared images	Infrared	PV panel	Handhold	336 × 256	No	67	Alfaro-Mejía et al. (2019)

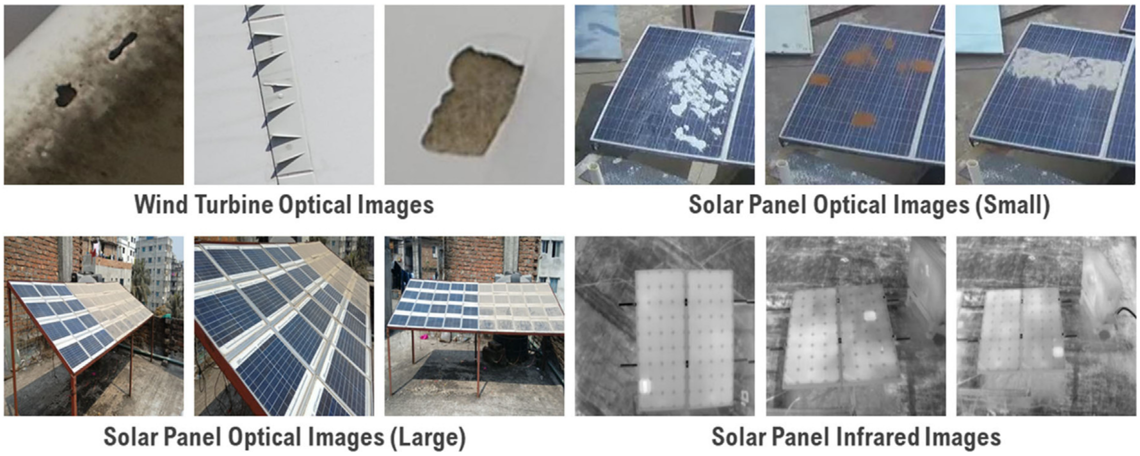

Fig. 3. Example of images in different image sets using in the experimentation of this work and presented as a general dataset.

3.2.3. *Solar panel optical images (large)*

This particular image set has 122 high-resolution long shots of 3264 × 1836 pixels dimension color images. These images are taken with a handheld camera and annotated as damages where PV panels are covered by dust.

3.2.4. *Solar panel infrared images*

Solar Panel Infrared Images are collected from Alfaro-Mejía et al. (2019) and annotated according to the snail trails and hot spot failures. In this image set, 67 images were acquired using a Zenmuse XT IR camera with a DJI Matrice 100 drone. All the images in the set are 336 × 256 pixels in dimension and grayscale.

3.3. *Drone mission planning*

For a single inspection, UAV missions could be planned considering the required flight time to cover a certain area with the help of spare batteries. The following drone mission planning or the conjecture provided in this regard are calculated from drone specifications by the manufacturer, but not based on any direct experimental data. In our case, the flight time of the DJI Mavic Air Pro 2 with three spare batteries can amount to a total of 93 min with 2 breaks in the middle. However, considering the spare time for repositioning the drones during changes of the batteries and extra energy consumption due to variable wind obstruction is estimated to be around 6 min each. The area covered by the drone from a position depends on the altitude of the drone and the field of view (FOV) of the mounted camera (Álvarez-Tey et al., 2017). Without wind, the DJI Mavic Air Pro 2 can fly 25 km per hour. Positioning the drone at 70 meters' altitude and with the mounted camera of a field of view 78.8 degrees, it can cover 3.19 acres' area in a single image. With the mission plan to line scan an area of 50 acres, the drone will have to travel a total of 29 km which will take around 69.6 min. Inspection at 70 meters altitude is required for wind turbine blades normally located at that height. The drones in that sense will be in closer proximity to the blade compared to ground distance. Other external factors (for example, lighting conditions, wind speed, air particles, reflectance of the surface, focusing on the damage, UAV stability, etc.), are involved in defining the quality of the acquired images as well.

For PV panel inspection, the drone could be at an altitude of 30 meters and it will take around 73.8 min to cover the 15 acres of land on a single day of mission planning. We may operate at an even lower altitude to capture details of smaller damage types at the cost of the lower area covered per battery usage.

Flight analysis and calculations of drones as a possible inspection method requires substantial experimental data and validation to support the conjecture which can be a part of the future scope.

3.4. *Mean average precision (MAP) as performance measure*

In this work, we detected the damages in terms of bounding boxes and compared them regarding the manual annotation in a similar format. Therefore, mean average precision is being used to evaluate the object detection performance during inference. A detection in terms of the bounding box is considered true positive if it overlaps with the ground truth (manual annotation) with more than a certain threshold. Intersection over Union (IoU) is used to measure the overlap of a prediction and the ground truth. IoU is defined as the following formulation.

$$IoU = \frac{P \cap GT}{P \cup GT} \tag{1}$$

Here P and GT are the predicted and ground truth bounding boxes respectively. If the value is more than a user-defined threshold which is in our case 0.5, the prediction is considered as a true positive. This 0.5 value is relatively conservative as it makes sure that the ground truth and detected object are very similar in terms of location, size, and shape. Per class precision for each image, P_C *is* calculated using Eq. (2). For each class, average precision, APC *is* measured over all the images in the dataset using Eq. (3). Finally, mean average precision (MAP), is measured as the mean of average precision for each class over all the classes in the dataset (see Eq. (4)). In this work, the MAP at 0.5 thresholds is reported in percentage in the rest of the article.

$$P_C = \frac{N(True\ Positive)_C}{N(Total\ Objects)_C} \tag{2}$$

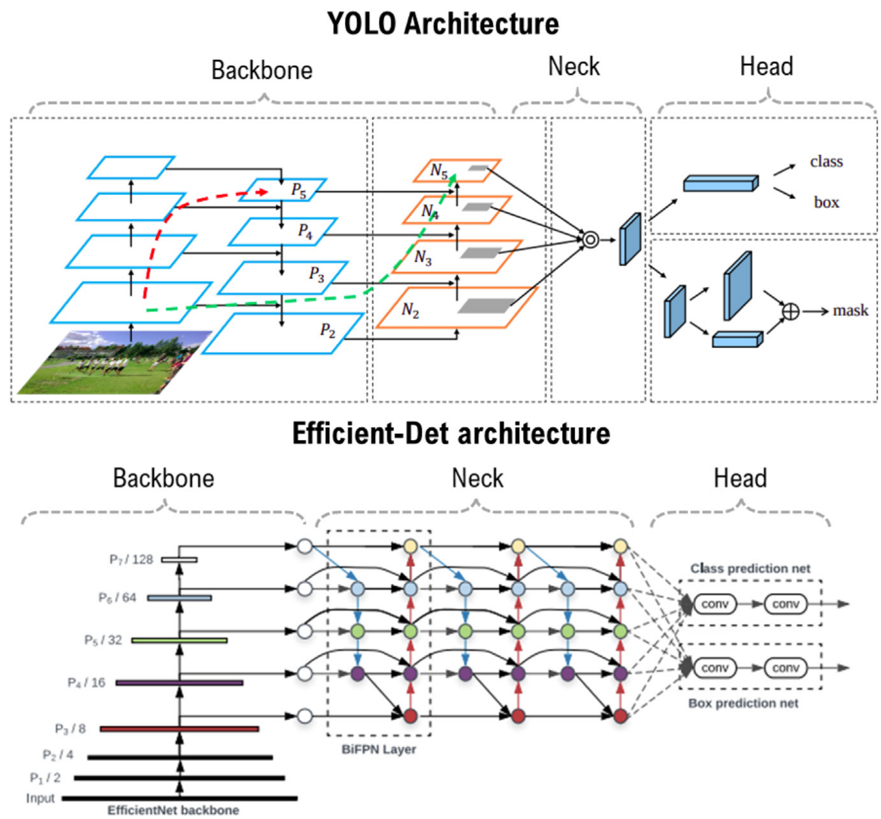

Fig. 4. Architectural differences in YOLOv5 and EfficientDet.

$$AP_C = \frac{\sum P_C}{N(Total\ Images)_C} \tag{3}$$

$$MAP = \frac{\sum AP_C}{N(Classes)} \tag{4}$$

3.5. Damage detection framework for training and inference

In this work, deep learning based approaches are extensive as explored as they are currently among the state-of-the-art result producers for many applications. Different stable meta-architectures are nowadays publicly available and have already been successfully deployed for inspection-related applications. Among deep learning object detection frameworks, the best-performing methods are EfficientDet (Tan et al., 2020), YOLOv3 (Redmon and Farhadi, 2018), YOLOv4 (Bochkovskiy et al., 2020), and YOLOv5 (Jocher et al., 2020). These methods are applied over six different combinations of damage datasets to detect damage with the performance matrix defined as MAP. The architectural differences between YOLOv5 and EfficientDet are shown in Fig. 4 (Jocher et al., 2020; Tan et al., 2020).

To analyze the impact on the detection precision of different object detection methods we have tried on six different configurations combining each of the four datasets described earlier. The experimental setups are: (1) Wind Turbine Optical Images (Wind Damage); (2) Solar Panel Small Optical images (Solar Small); (3) Solar Panel Small and Large Optical Images (Solar Small + Large Solar); (4) Solar panel Small and Infrared Optical Images (Solar Small + IR Solar); (5) Solar panel Small, Large and Infrared Images Optical Images (Solar Small + Solar Large + IR Solar); (6) Wind Turbine, Solar panel Small, Large and Infrared Optical Images (Wind Damage + Solar Small + Large Solar + IR Solar).

We have evaluated the performance based on Mean Average Precision (MAP) on four different datasets as described 3.2. For each combination, we trained the network for a 100 epoch initiated from a model that was pre-trained on the COCO dataset. In each epoch, all of the training samples are used once to update the model weights.

4. Results and evaluation

4.1. Experimental results

All the experiments were performed on a Google Cloud machine with a Geforce K100 graphics card with 16 GB VRAM on a Linux operating system. The time required for 100 epochs training with the EfficentDet D0 to D5, YOLOv3, YOLOv4, and YOLOv5 with best-performing augmentation configuration is approximately 5 h respectively. For training, we used 100 epochs in each run during optimization and 0.5 intersections over union (IOU) as the threshold for correct detections. The dataset was split into an 80–20 ratio for training and validation.

Inference time depends on the size of the input image and the depth of the CNN architecture used. In our case, the average time required for inferring a high-resolution image using the EfficentDet (D0 to D5), YOLOv3, YOLOv4, and YOLOv5 networks after loading the model are approximately 2 s respectively. Table 2 shows the comparative analysis of the different deep learning object detection frameworks and dataset combinations in terms of MAP at the 0.5 thresholds. Fig. 5 illustrates the trends in AP performances among different models across a varied combination of datasets. Fig. 6 presents the example of damage detection on test images.

From the results, it can be seen that in all the cases the highest MAP is received from the deepest network from its genres such as EfficientDet-D5 and YOLOv5. Whenever there are wind damages introduced in the mixing of the dataset YOLOv5 tends to performs better. YOLOv5 being the deepest network with the highest

Table 2
Comparative analysis of the different deep learning object detection frameworks and dataset combination in terms of MAP at 0.5 threshold.

Models	Wind Damage	Solar Small	Solar Small + IR Solar	Solar Small + Large Solar	Solar Small + Solar Large + IR Solar	Wind Damage + Solar Small + Large Solar + IR Solar
EfficientDet-D0	0.796	0.749	0.705	0.808	0.731	0.839
EfficientDet-D1	0.797	0.751	0.704	0.810	0.723	0.848
EfficientDet-D2	0.798	0.756	0.693	0.821	0.726	0.831
EfficientDet-D3	0.809	0.759	0.697	0.834	0.738	0.845
EfficientDet-D4	0.811	0.761	0.703	0.848	0.751	0.827
EfficientDet-D5	0.821	**0.764**	**0.711**	**0.861**	**0.766**	0.853
YOLOv3	0.766	0.701	0.684	0.786	0.742	0.862
YOLOv4	0.789	0.734	0.681	0.803	0.735	0.864
YOLOv5	**0.866**	0.743	0.695	0.816	0.762	**0.873**

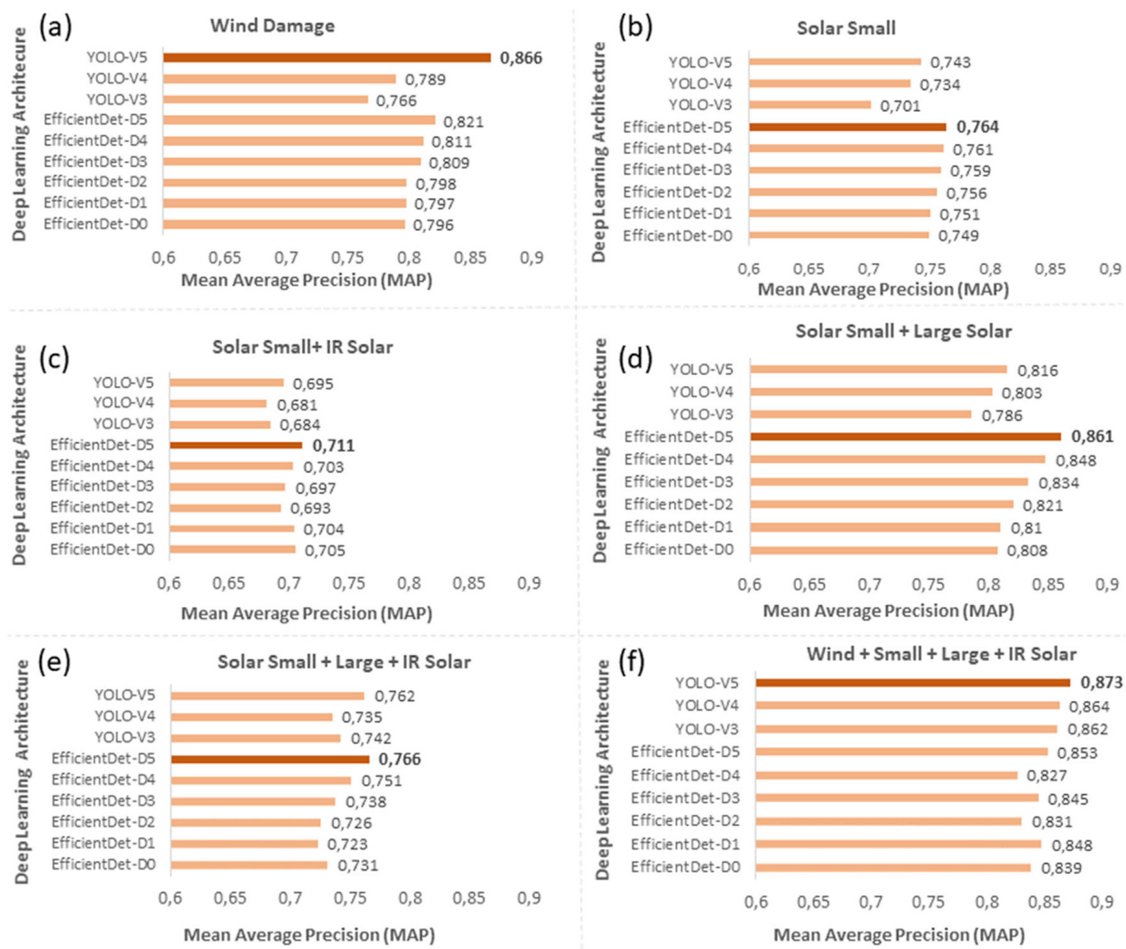

Fig. 5. MAP performances among different models across the varied combination of datasets.

number of parameters (as shown in Table 3) can encapsulate important class details during learning. Another interesting find from the results is when the mixing of the dataset (that is the 6th configuration) is the highest, the network scored the highest MAP for each network. This means that with an increase in the size of the dataset, the network can learn higher-dimensional features of the object better and also gather a substantial amount of knowledge about possible backgrounds. This is true for all models starting from EfficientDet-D0 till YOLOv5. If we further analyze the bounding boxes in Fig. 6, it can be observed that the bounding boxes are quite accurate even when tested in varied scales, drone angles, sensor modality, etc. These results in terms of bounding boxes can be post examined to know the severity and condition of the damages. Their locations relative to the overall structure is a strong indicator of the severity of the damages.

In this work, we have reported the performance measures on the validation set in the corresponding result tables (Tables 2 and 3). The overall MAP of the combination of each data set and recent object detection models are duly reported and in almost all the cases, scored above 0.8. The overall MAP, which allows comparing with other object detection schemes, and contrast based on the data set used are reported in Fig. 5. In this work, as an evaluation metric, we primarily focus on precision, as it is of utmost importance to detect the damages as much as possible. If there are some false positives, they could be removed with further manual checking, thereby significantly reducing the workload of field experts. We suggest using the whole automated system as a suggestion aid to human experts to make the final decision. In that case, the human, rather than scanning the entire picture, can re-evaluate a few potential areas of damages and provide the final verdict.

Fig. 6. Example of damage detection test images using the model YOLOv5 trained on Wind Damage.

Table 3
Records of number of parameters, FLOPs, and MAP for different compared methods.

Model	Parameters	FLOPs	MAP
EfficientDet-D0	3.9M	2.5B	0.839
EfficientDet-D1	6.6M	6.1B	0.848
EfficientDet-D2	8.1M	11B	0.831
EfficientDet-D3	12M	25B	0.845
EfficientDet-D4	21M	55B	0.827
EfficientDet-D5	34M	135B	0.853
YOLOv3	63.M	71B	0.862
YOLOv4	27.6M	52B	0.864
YOLOv5	89.0M	166.4B	0.873

4.2. Discussion

The experimental results of this work show that, for the used six different combinations of optical image datasets, the performance is more sensitive to the quantity and quality of the image (considering image augmentation) than the selection of CNN architecture. One of the main reasons is that different types of damage can have considerably different appearances considering data sources. Thus, different object detection methods need a significant number of examples to learn from. As a result, for the case of the combined four image dataset, the detection precision in MAP is higher compare to the smaller damage dataset. Also, one of the important considerations in selecting any deep learning architecture for object detection purposes is the amount of complexity or the hardware requirements that come with it. In Fig. 7, we can see that some of the networks like YOLOv5 are very accurate, but very resource hungry as well. Whereas YOLOv4 can be a better design choice, as with three times fewer parameters it can produce an almost similar level of precision in detection. Fig. 7 in general illustrates the relationship between precision and parameter requirements or hardware requirements of the architectures tested in this work.

4.3. Future works and limitation

The trained model from this work with some system integration can be readily used to detect objects and damages from drone based power plant inspection images. With the state-of-the-art deep learning techniques, we achieved on average 80% or above mean average precision (MAP) with conservative true positive detection criteria, which can be further increased with augmentation during inference and also using the information from overlapping images. The proposed system can replace or at least largely facilitate the manual damage annotation by experts which is time-consuming and expensive. In addition, the automated system is characterized by being reproducible and deterministic. However, one of the issues with deep learning based models is they are very data-hungry. With more data and examples of damages from varied backgrounds, shares, sizes, and resolutions, the model can become much more robust and work as a backbone for reliable useful applications.

In this work, with deeper networks and fewer examples to train from, over-fitting can also become an issue after a large number of epochs. For this, we train the models over 100 epochs to monitor overall damage detection performance. In future work, we plan to utilize a generalized CNN architecture for different types of optical image datasets.

For other types of power plants, we need to retrain the model using transfer learning for new classes of damages. Also, the reporting systems that are based on data monitoring needs to get adjusted according to the requirements at hand. For wind turbines, drones acquired images sideways, whereas for solar plants the images need to be acquired top-down, however from an analysis method point of view, it will have no impact on the performance in general.

The automated image based detection system proposed in this work depends a lot on the quality of the high-resolution inspection images using drone based monitoring. There are several modalities and design considerations for this kind of sophisticated inspection method which need to be carefully chosen and deployed (Rakha and Gorodetsky, 2018). The entire pipeline from acquisition till final decision-making should work in coherence and adapt with constant changes in the technology and market demand (Seo et al., 2018).

5. Conclusion

The cost of renewable energy installation maintenance for ensuring safety and reducing production loss can be significantly reduced using automated damage detection based on routinely acquired drone inspection images. This work explored four different datasets and six different dataset combinations to perform experimentation of state-of-the-art object detection architectures. The results show that with advanced deep learning architectures, the models can learn to recognize damages with precise bounding boxes even when the damages are from varied structures, acquired with different sensors, and possess longer ranges shapes, sizes, viewpoints, and other external artifacts. This work is the

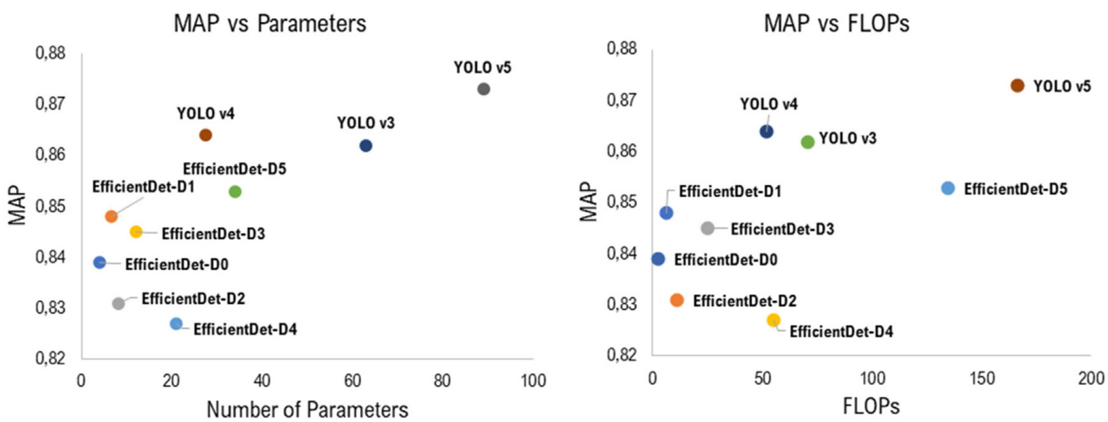

Fig. 7. Comparison of the number of required parameters and FLOPs among compared methods based on their respective MAPs.

first of its kind to produce a generalized model for training across all kinds of renewable power plant structures, producing state-of-the-art results on the published dataset. The dataset itself is also a contribution from this work for the research community. The trained models can work as a core for future applications to foster regular, automated, and reliable inspection of power plants. These types of smart inspection systems will reduce the maintenance cost significantly, and also increase the durability and lifetime of large power plant installations.

Abbreviations

The following abbreviations are used in this manuscript:

PV	Photo Voltaic
WT	Wind Turbine
UN	United Nations
LE	Leading Edge Erosion
IEA	International Energy Agency
YOLO	You Only Look Once
CNN	Convolutional Neural Network
IoU	Intersection over Union
MAP	Mean Average Precision

CRediT authorship contribution statement

ASM Shihavuddin: Conceptualization, Software, Data curation, Writing – original draft, Supervision, Project administration. **Mohammad Rifat Ahmmad Rashid:** Methodology, Software, Writing – original draft. **Md Hasan Maruf:** Methodology, Investigation, Writing – original draft, Visualization. **Muhammad Abul Hasan:** Validation, Formal analysis, Investigation, Writing – review & editing, Visualization. **Mohammad Asif ul Haq:** Validation, Formal analysis, Writing – review & editing. **Ratil H. Ashique:** Validation, Writing – review & editing. **Ahmed Al Mansur:** Conceptualization, Resources, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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