Wind Turbine Blade Surface Damage Detection based on Aerial Imagery and VGG16-RCNN Framework
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Abstract—In this manuscript, an image analytics based deep learning framework for wind turbine blade surface damage detection is proposed. Turbine blade(s) which carry approximately one-third of a turbine weight are susceptible to damage and can cause sudden malfunction of a grid-connected wind energy conversion system. The surface damage detection of wind turbine blade requires a large dataset so as to detect a type of damage at an early stage. Turbine blade images are captured via aerial imagery. Upon inspection, it is found that the image dataset was limited and hence image augmentation is applied to improve blade image dataset. The approach is modeled as a multi-class supervised learning problem and deep learning methods like Convolutional neural network (CNN), VGG16-RCNN and AlexNet are tested for determining the potential capability of turbine blade surface damage.

Index Terms—AlexNet, Blade surface, Computer vision, Convolutional neural network, Deep learning, Image augmentation, VGG16-RCNN, Keras

I. INTRODUCTION

WIND energy is quite possibly the most encouraging sustainable power source that emanates next to zero natural contamination. Wind turbines harness active energy from the breeze and convert it into an electrical force. The introduced limit of wind power age in India is the fourth biggest on the planet — just China, the USA, and Germany are ahead. Wind power represents almost 10% of India’s absolute power usage limit, which currently accounts for 4% of total power. With an installed capacity of 38,785 MW (March 2021) of wind power, India generated around 59.8 TWh of energy in the year 2020-2021. Renewable energy sources (barring enormous Hydro) presently represent 24.7% of India’s in general introduced power limit of 382151 MW [1]. Wind energy holds the significant segment of 41.5% of all out RE limit (94434 MW) among the sustainable and proceeded as the biggest provider of clean energy.

Wind turbines work on a basic guideline, rather than utilizing power to make wind like a fan, wind turbines utilize the breeze to produce power. Wind turbines consist of rotatory and non-rotatory components such as base, tower and foundation, nacelle, and rotor and rotor blades. The breeze turns the propeller-like sharp edges of a turbine around a rotor, which in turn rotates a generator thereby producing electrical power. The blades being the most important for harnessing wind energy needs to be maintained in perfect shape. Accumulation of bugs, oil, dust, and ice on the blades reduces power as much as 40% of the rated turbine power. Literature suggests that operation and maintenance (O&M) cost for a wind turbine accounts up to 30% of wind power generation cost [1]. Wind turbine edges present a particular test and there are various edge damages that can occur through the lifetime of a wind turbine. Turbine edge damage is probably the costliest as far as the O&M cost is concerned. Most of the force of the turbine is created towards the main edge and at the tips of the cutting edges. In this manner, it is imperative to keep them very much kept up. Cutting edge damage can make unexpected primary disappointment and the related costs to fix them are high. For the most part, trauma to wind edges can emerge because of assembling deformities, precipitation, and flotsam and jetsam, water entrance, variable stacking because of wind, operational mistakes, lightning strikes, and fire. Early recognition and alleviation procedures are needed to keep away from or lessen damage to expensive breeze turbine edges.

The productivity, support, and downtime expenses of the wind turbine could be improved by executing a condition monitoring task. This task is essentially designed to handle sensitive equipments of a wind turbine. Thus, with this approach, a condition monitoring and fault diagnostic framework for a wind turbine can guide operator to take important decisions. Researchers in various fields attempt to foster calculations that gain proficiency with the conduct of the given issue utilizing verifiable information from historical analysis [2], [3], [4]. Learning algorithms can be utilized for various applications, for example, forecasting the time-series behaviour of a turbine variable like gearbox oil and bearing temperature [5]. In this manuscript, we focus on the wind turbine blade surface damage detection as the primary condition monitoring task to alleviate scenarios of catastrophic damage(s) in a given wind farm.

To a significant degree, sharp edge defects are responsible for around one-fifth of the issues observed during the operational existence of the breeze ranch [6]. At present, drone’s high-resolution photographs on location or manual review are utilized to identify a potential damage and this procedure is followed after a year long study of edge deformity. However, in the worst case scenario, an edge disappointment can mean significant expenditure to fix and substitute the existing blade thus leading to an increased turbine downtime. Further, infor-
mation retrieval from a damaged wind turbine blade in form of high resolution images requires sufficient memory space and with the manual inspection of these images, error rate in diagnosing the damage may reach a high value. Automating the turbine blade surface damage detection means reducing the on-site man hours but at the same time it requires skilled labor to operate and deal with the aerial imagery via drones.

There are various condition monitoring strategies for wind turbine to investigate its sensitive rotatory and non-rotatory parts. In [7], a diagnostic method for turbine blade health is proposed based on a system of high fidelity optical and wireless sensor networks (WSNs). Field measurements are carried out where the multivariate data from sensory circuits is transferred to corroborate the authenticity of the same. Further, in order to deal with extreme environmental conditions surrounding the rotor, optical Fiber Bragg Grating (FBG) sensors are deployed which provide several advantages in form of space constraints. Another strategy for both condition monitoring and damage area detection of wind turbine edges by frequency response transmissibility is proposed in [8]. The technique uses the CM signals estimated by various adjoining sensors in wind turbines. Results reveal in accurate damage detection along with its position. However, this does not help in ice and snow build-up in turbine blades. In [9], MEMS sensors are utilized in the damage expectation of edges which addresses worldwide observing methodology where the entirety the edge is under investigation.

Literature pertaining to surface damage detection of wind turbine blade via aerial imagery is limited. Wang et al. [10] utilized drone pictures for damage like crack identification. To naturally remove harm data, they utilized Haar-like highlights and group classifiers chose from a set of base models including logitBoost, decision trees, and support vector machines. Their work was restricted to recognizing the break in the blade and was based on archaic machine learning algorithms. In [10], a technique for location of surface breaks in wind turbine edges based on UAV pictures is proposed. A sliding window strategy was utilized to distinguish breaks in the picture of the edge. The field of computer vision and deep learning seems to be proficient and well known, giving noteworthy insights in the predictive maintenance of wind turbines. Thus, in this manuscript We have tried to address the issue of blade surface damage detection by formulating an image analytics based multi-class classification setup. The advantages of image analytics based blade health management include: (i) reduced human effort, (ii) frequent turbine supervision, and (iii) accurate information retrieval via aerial imagery. Human errors which otherwise cause delayed turbine inspection can now be easily dealt with aerial imagery based data-acquisition of wind turbine blades. The main contributions of this work can be summarized as follows:

(i) Aerial imagery based wind turbine blade surface damage detection is proposed. Images collected via drone are pre-processed to ascertain the quality of image dataset. Image augmentation is leveraged for enhanced deep learning based training process for detecting blade damage.

(ii) Deep learning algorithms like convolutional neural network (CNN), VGG16-RCNN, and AlexNet are tested for their potential capability to discriminate various types of blade surface damages.

(iii) The ability of transfer learning models such as VGG16-RCNN and AlexNet to yield a low missed failure and false positive rate is reported. This enhances the reliability of the aerial imagery based wind turbine blade inspection for potential damages.

II. DEEP LEARNING FOR COMPUTER VISION

Computer vision is a branch of artificial intelligence which deals with visual inspection and investigation. It is frequently used in medical diagnosis, facial recognition, and supervision industrial components and systems. In the present case, a computer vision based deep learning framework is proposed for turbine blade surface damage detection. The wind turbine blade images captured by a drone are in high resolution and needs to be trimmed down to feed to deep learning models for feature extraction. Since the blade surface damage is very critical for a wind turbine operation, efficient extraction and size of the data is important in accurate classification and detection.

An end to end method of extracting the features layer by layer shows descriptive results of faults in object detection than selecting the images. Deep learning proposed methods help provide such substantial results because of its value sharing mechanism. The extraction of the defects in the blade images is an important step in order to analyze the faults and defect features. The main aim of CNN is to run these images within the convolutional layer and pooling layer. The feature extraction is basically a sequence of these two layers being fully connected. In the case of blade images, the feature selection is done in a cleaner manner and with a local perspective of dividing the images as classes for its target recognition. When extensive pre-processing is to be avoided and raw data is to be used, this network design has been utilised to image classification in particular, images must be categorised directly. The first layer usually extracts basic features such as horizontal or diagonal edges. This output is passed on to the next layer which detects more complex features such as corners or combinational edges. As we move deeper into the network it can identify even more complex features. It aims to minimise the image’s real input size by using augmentation and recognising the image’s significant features. Convolution, as illustrated in the Fig. 1 decreases the size of a picture by roughly thrice depending on the number of feature detectors used and the procedure used. The feature maps of the given image are obtained by convolving the input images with the input parameter (feature filter) values as designed. The activation layer, pooling layer, and fully automated layer are the other layers available in the CNN based classification process. The annotation data is used to transform the data, and train it according to the parameter values chosen for the dataset.
Fig. 1: Convolutional neural network architecture for wind turbine blade damage detection

Similarly, a VGG16-RCNN [11] model architecture uses 16 convolutional layers with initial input image size of 224 × 224 with 64 channels of kernel size of 3 × 3. VGG16-RCNN is a convolutional neural network that converts the RGB images into features and extracts the areas detecting those features. In the present case, these features include erosion, damage, and edgy surfaces. It makes the improvement over AlexNet by replacing large kernel-sized filters with multiple 3 × 3 kernel-sized filters one after another. VGG16-RCNN shows the highest accuracy percentage as compared to the rest of the models.

AlexNet model implemented in this study is based on the AlexNet transfer learning model [12]. The fundamental structure is made up of five convolutional structures and three fully connected layers. The features extracted from AlexNet’s first five layers of training in the features the image folders are sub-classified in. In the three fully connected layers, the previous two fully connected layers output more abstract features. Despite the fact that the images of the blades with surface defects differ significantly from those in the Damage or erosion dataset, the previous five convolutional structures trained in the dataset can still extract the local features of the blade surface defects. AlexNet architecture is used for any object detection problem, showing more than 50% results than that of the basic CNN architectures.

III. DESCRIPTION OF BLADE IMAGE DATASET

The dataset used for this research work is acquired from Mendeley- Drone inspection images of a wind turbine [13]. Common defect areas on which we have focused in this work include erosion area, edge area, reference area, and damage area. Fig. 4 and 5 depict different types of the damaged area of wind turbine blade. Reference area as shown in the images is treated as a normal image in the multi-class classification setup.

![Damaged area](image1.png)  ![Edge area](image2.png)

**Fig. 4: Damaged and edge area for wind turbine blade**

![Erosion area](image3.png)  ![Reference area](image4.png)

**Fig. 5: Erosion and reference area for wind turbine blade**

The included dataset was utilized for testing and assessment of structure from motion calculations for 3D remaking, as information for ML algorithms for recognizing damaged regions on edges or for evaluating edge surface unpleasantness. Pictures are taken utilizing a high-resolution camera with a resolution of 8688 x 5792. This dataset contains 4 wind turbine blade patches of spaces of various surface designs. One of the patches are of damaged regions, one of the patches are of erosion regions, without articulated surface defect and one
of the patches is a reference region, that doesn’t contain any unpleasantness or damage. The last fix contains the entire of the blade’s edge region and is involved a blend of seriously damaged regions, spaces of little roughness, and clear regions. The dataset initially had few images (168) and hence in particular the classification approach was suffering from class imbalance. To solve this, image augmentation is carried out on the entire dataset. Augmentation of images is a strategy that can be utilized to grow the size of the dataset by making altered forms of pictures in the dataset. Training deep learning models on a large dataset can yield skillful models, and the augmentation method can create differences in the image dataset size that can enhance the ability of a model to classify accurately. Fig. 6 shows the image after augmentation.

(i) Height_shift_range for an upward shift of picture and width_shift_range for a level shift of picture. In the event that the worth is a float number, that would show the level of width or tallness of the picture to move. If not, on the off chance that it is a number worth, essentially the width or height are moved by those numerous pixel esteem. Measure used for both height and width shift is 0.3.

(ii) Property called rotation_range permits you to arbitrarily pivot pictures through any degree somewhere in the range of 0 and 360 by giving a number worth in the rotation_range contention. Measure used for this property is 45.

(iii) Horizontal_flip and vertical_flip for flipping along the vertical or the level pivot. Here, we have set true for both vertical and horizontal flips.

(iv) Zoom_range is used for zooming. Any worth more modest than 1 will focus in on the picture. Though any worth more prominent than 1 will zoom out on the picture. We have used value 0.2 as zoom_range which is performing zoom in for the given images.

(v) At the point when the picture is turned, a few pixels will move outside the picture and leave a vacant region that should be filled in. Using fill_mode property if ImageDataGenerator with the default value of “nearest” we have replaced the empty area with the nearest pixel values.

Properties of augmentation which are being used for the image are rotation, width-wise shift, height-wise shift, horizontal and vertical flip with zoom range. Before augmentation size of the dataset (number of images per class) was very small, but once augmentation was applied dataset size was increased and on that new augmented dataset. The keras neural network library in Python is capable of transforming the images to a version where it is easy to apply the training model over it. The less the data size of the set, it is faster to run the models over the datasets. Image Augmentation is a method on how to change the input image by certain parameters to teach the network that all images are the same regardless of the changes made. Fig. 4 and 5 illustrate the original images for different classes (or blade conditions) while Fig. 6 depicts the augmented images where the target area is zoomed and cropped accordingly.

IV. EXPERIMENTAL RESULTS

Wind energy is a strong contender in the market of renewable sources of energy. In order to collect the wind’s energy in a more efficient way. As a result, there is a high probability of damage, which is associated with the work. Thus, there is a constant demand of monitoring the blades, it will reduce the cost of operation and maintenance. Image data is the most important requirement for training a CNN model. More the data available, we can train the neural network(s) efficiently and accurately in damage classification and detection tasks. In this neural network training, we use multi-class classification based approach for wind turbine blade surface damage detection. The image data obtained from aerial imagery is deemed to classify into four classes. Multi-class classification helps the CNN model to get an idea of the extent of the damage and thereby providing insights of the damage category. Fig. 7 illustrates the image analytics based turbine blade surface damage detection framework. A drone collects the high-resolution images of turbine blades and transmits them wirelessly to a server.

Fig. 7: Image analytics based wind turbine blade surface damage detection framework

In deep learning, it is necessary for thousands of training samples to be representative of the presentation of the designs to have a good detection model. Images captured by the drones of the size $8868 \times 5792$ pixels which cannot be directly used to train a given deep learning model. These images were classified into four classes namely, Damage Area, Erosion Area, Edge Area, and Reference Area. For the model to be trained more accurately, the images which were having the damage classes were cropped, annotated (classified) on its particular damage class, augmented and used to train the model. This similar procedure was performed on the remaining
As discussed in the previous section, CNN is the base model for image processing with extensive pre-processing CNN is the base over which other predefined models are built. In terms of performance and accuracy other models such as Mask RCNN, Fast CNN, Faster RCNN, VGG16-RCNN and AlexNet show varied and better performance than the CNN framework. In this manuscript, apart from the CNN, VGG16-RCNN and AlexNet is also implemented to show the comparisons among the three models. VGG16-RCNN can be defined as the first best model used for image processing and it next comes AlexNet.

| Class             | Total Images | Training Images | Validation Images |
|-------------------|--------------|-----------------|-------------------|
| Damage Surface    | 234          | 187             | 47                |
| Erosion Surface   | 195          | 156             | 39                |
| Edge Surface      | 90           | 72              | 18                |
| Reference Surface | 240          | 192             | 48                |

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V. CONCLUSION

Wind turbine blade is an important rotatory component that plays a critical role in harnessing energy from the moving air. Largely, the O&M procedure(s) for wind turbine(s) include condition monitoring techniques where the individual turbine component is assessed for failure diagnosis. In this manuscript, one such component, that is, the wind turbine rotor blade is assessed for its surface damage via image analytics. Wind turbine blade images are considered in different damage scenarios and are treated for multi-class classification setup. The initial image(s) are treated with canny edge detector and bounding boxes formed thereafter are cropped to feed the resized images to deep learning image classification model. Three models, namely, VGG16-RCNN, CNN and AlexNet are considered and yield an accuracy of 93.8%, 90.7% and 74.1% respectively. It is interesting to consider the false positive rate as a major parameter to raise alerts to farm operator.

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