Deployment of AI technologies in Wind Energy Industry Sector

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Abstract

This paper aims to evaluate the implementation of Non-Destructive Inspection Techniques (NDIT) in the wind energy sector. For this purpose, a use case where AI-enhanced vision algorithms for anomaly detection in the painting inspection process in the wind energy sector is presented. Limitations and criteria for selecting the optimal hardware will be discussed, as well as the different parameters used for selecting, training, testing and validating machine vision applications in this field. Finally, the evaluation metrics of the algorithm used to evaluate the confidence level of the proposed model are explained, its performance on real, unseen data is presented, and future lines of action, as well as potential alternative applications, are summarized.

Keywords

Non-Destructive Inspection Technologies, Acoustic Emissions, Zero Waste, Zero Defects, Quality Assurance, Inspection as a Service (IaaS), Sustainable Development Goals

1. Introduction

The use of Non-Destructive Inspection Technologies (NDIT), as opposed to traditional destructive procedures, brings numerous benefits, including the competitive advantage of automating the manual inspection processes currently used in many industrial processes [1]. Currently, conventional methods based on visual inspections that require the human factor may be influenced by subjective factors that do not allow standardization, such as experience in the inspection process, the operator's level of training and visual fatigue, among others [2].

In this context, the use of artificial intelligence (AI) systems allows to solve and automate classification and prediction problems in the industrial environment. Integrating NDIT with Artificial Intelligence (AI) applications is a zero-defect strategy to improve first-time right rates in production environments [3], [4]. Also, deploying NDIT for real-time quality assurance requires a collaborative approach for integrating and interoperability with the cyber-physical system for quality inspection deployment in an industrial production environment. Exploiting these technologies in the wind European industry is essential for achieving sustainable production, waste reduction and enhance the decision-making processes in manufacturing quality assurance [5]. In addition, by employing technologies under a common unified framework and through platforms such as the one offered by Zero Defects Zero Waste (ZDZW), it allows the creation of collaborative networks that enable the

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sharing of advances in innovation and production in leading companies in the global wind energy sector [6], [7].

1.1.EU Wind Energy Sector

New policies supported by the European Union based on the 2030 agenda and climate target plan foster wind energy generation in the coming years [8]. The EU Green Deal further establishes the ambitious objective of transforming Europe into the world's first emission-neutral continent [9]. Based on this commitment to the Climate Plan, whose target is to achieve a 55% greenhouse gas reduction, the expansion of renewable energy sources in the European Union is inevitable, constituting 37.5% of overall energy generation, encompassing various technologies, with wind energy contributing significantly at 37.3% in 2021 [10]. The importance of wind energy generation can be observed in the increase in installed capacity, which has increased over the past ten years from 110 GW to 261 GW [11]. It must be noted that the evolution and growth are primarily due to various factors such as decreasing costs in renewable electricity from solar PV and wind power, dropping in ten years by nearly 75-50% [12].

Within this energy transition framework, current research focuses on meeting the demand for faster, more efficient, and more accurate quality inspection services in the wind energy industry that align with the zero defects and zero waste (ZDZW) framework. Implementing NDIT for real-time inspection can reduce material and energy consumption and lead times through higher inspection rates and a reliable automatic inspection process while improving overall operational costs. The increase in operational performance will be achieved through reduced energy and materials consumption, improved quality, and reduced labor thanks to automatic inspection solutions, making the EU's wind energy industry more resilient and competitive.

1.2.Sustainable Development Goals

Integrating Artificial Intelligence (AI) into the European wind energy sector establishes a robust connection with several other SDGs, underlining the multifaceted impact of this technological advancement. The recent development of artificial intelligence (AI) in the European wind energy sector aligns seamlessly with the Sustainable Development Goals [13]. This technological development contributes directly to enhancing industrial processes' efficiency and sustainability, making cleaner and more efficient energy production processes possible.

By including non-destructive techniques and inspection algorithms within the European wind energy sector, process times and costs are reduced for the generation of resources that contribute directly to the European wind energy generation capacity (SDG 7 'Affordable and Clean Energy') and indirectly to the optimization of material and energy resources (SDG 13 'Climate Action') while encouraging the practice and integration of these systems that promote innovation in the industrial sector (SDG 9, Industry, Innovation and Infrastructure). It must be noted that integrating machine vision systems in industrial environments with harmful particles in suspension, as occurs in the painting process, increases safety in the inspection operations by mitigating the risks associated with manual labor while promoting the training and creation of new jobs related to AI (SDG 8 'Decent Work and Economic Growth'). Finally, collaboration between technology developers, energy producers, and policymakers is fostered thanks to AI integrations (SDG 17 'Partnership for the goals'). Partnerships forged through shared objectives, technological advancements, law-making and knowledge exchange are essential.

1.3.Use Case Scenario

The deployment of automated inspection systems represents an innovation in the quality assurance policies in manufacturing steel towers for wind energy equipment, whose goal is the implementation of new approaches such as zero defect and zero waste methodologies. Currently, the paint inspection process is carried out manually by operators inside the painting cabin, so it ends up being a repetitive task based on the subjectivity of each operator and visual fatigue due to the inspection of large objects during significant periods. Implementing automated inspection systems reduces human fatigue associated with manual labor, ensuring consistent attention to detail throughout the painting process. The vision systems based on artificial vision improve reliability and accuracy in detecting anomalies, which are required to comply with Original Equipment Manufacturer (OEM) quality standards of the wind energy sector.

2. Artificial Vision System

The efficacy of the AI-enhanced vision system has received considerable attention over the last years [14], [15], thanks mainly to recent advancements in computer vision algorithms for real-time object detection and segmentation models. The proposed artificial vision system has been designed to operate within a critical working distance defined in the range between 50 and 54 cm. This working distance specification is driven by the system's requirements to identify anomalies in the painting inspection process. The image acquisition system selected for the current use case is the Basler acA5472-5gc camera, which uses the Sony IMX183 sensor of 5472x3648 pixel. Besides, the vision system is completed with 25 mm focal length lens which provides for a field of view (FOV) of around 30 cm in width and 20 cm in height (giving around 18 px/mm of spatial resolution). Therefore, this configuration ensures full coverage and time reduction for the inspection area while enabling the system to discern defects ranging from 1 mm up to 1 cm. Deploying up to six cameras strategically mounted on an autonomous robotic platform makes the quality inspection process more efficient and faster.

2.1. Artificial Intelligence algorithm for painting inspection

The adequate neural network and model selection depends on the trade-off between computational resources and accuracy requirements. It is within this framework where YOLOv8 capabilities are presented is a state-of-the-art object detection algorithm known for its real-time processing capabilities and enhanced accuracy and speed in the detection of painting defects in real-time applications [16], [17], [18], [19]. This vision aligns with the objectives of ZDZW, whose inspection suites are designed to provide robust support for anomaly detection by relying on extensively customized datasets and machine-learning algorithms for comprehensive analysis. In the current industrial use-case scenario, the algorithm YOLOv8n was selected because it presents a better response in the inference speed (Table 1).

Table 1
Performance parameters depending on the neural network and model selected. (Adapted from: Ultralytics)

Model	Params (M)	FLOPs (B)	Size (pixels)	mAP (50-95)*	Speed (ms)**
YOLOv8n	3.2	8.7	640	37.3	0.99
YOLOv8s	11.2	28.6	640	44.9	1.20
YOLOv8m	25.9	78.9	640	50.2	1.83
YOLOv8l	43.7	165.2	640	52.9	2.39
YOLOv8x	68.2	257.8	640	53.9	3.53

* mAP values for single-model single scale on COCO val2017 dataset ** Speed averaged over COCO val images using a A100 TensorRT

2.2. Data Acquisition

Achieving higher levels of accuracy and reliability for Artificial Vision systems requires specific model training and high-quality data. The use case scenario dataset encompasses diverse scenarios, replicating real-world conditions along the manufacturing process. The model objective lies in detecting the six most recurrent defects within the painting process. Pinholes, blistering, inclusions, scratches, delamination and crumples are identified as critical defect classes, each with distinct characteristics and implications for the quality of the painted surface (Figure 1). The dataset utilized for the development and fine-tuning of the YOLOv8 model has undergone significant expansion throughout model iterations. Initially comprising 299 annotated anomalies, the dataset has grown to incorporate 401 annotated anomalies in its latest version, allowing the model to learn and generalize from a more diverse set of anomaly instances. However, more than 85% of the images used for training are anomalies of the inclusion type, resulting in a phenomenon known as sampling bias.

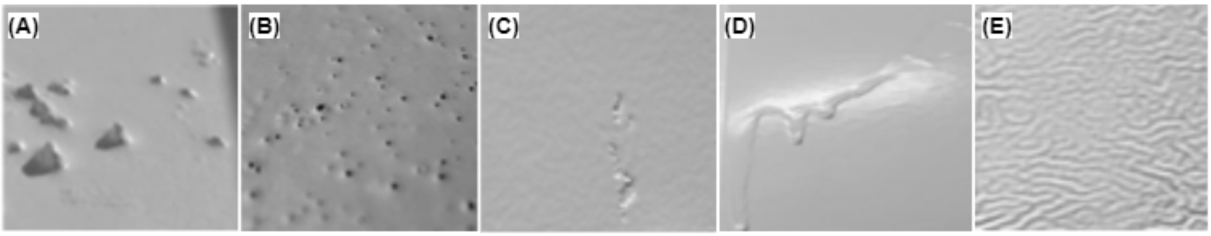

Figure 1 Painting defects on wind tower section: (A) inclusion, (B) pinhole, (C) scratches, (D) delamination and (E) crumple.

2.3.Model Training Methodology

Once the data acquisition for the use case is performed, all these images are annotated using squared Bounding Boxes (BB) that enable the anomaly location within the image. To use the dataset in a suitable way, it is subdivided into three categories: train, test and validation using 70%, 20% and 10% of the images in the dataset, respectively (Table 2). The training hyperparameters selected for the current study determine a batch size of 16 images, 200 epochs, considering that the training stops if there is no improvement in the last 50 epochs. The remaining parameters have been set to their default value for the training process. At the hardware level, the resources that have been allocated for training correspond to NVIDIA RTX 3090 24 GB x1, 525.60.11 drivers & CUDA 12.0, MSI Z270 (MS-7A63); 32 GB and Intel i7-7700K (4.2 GHz).

Table 2
Dataset arranged in categories for model training.

Iteration	Train	Validation	Test	Total
1st iteration	185 (62%)	38 (13%)	76 (25%)	299
2nd iteration	290 (72%)	50 (12%)	61 (15%)	401

3. Artificial Vision System

For the evaluation of the trained model in both iterations, it is represented by the Average Precision (AP) to measure the prediction accuracy and Intersection over Union (IoU) to measure the overlap between two BBs. An IoU limit over 50% is defined to determine whether a prediction is regarded as truth. For the presented use case, maximum mAP50 and mAP50-95 metrics achieved during training were collected and summarized (Table 3). The results show that an increase of 100 images with defects in the training set improved the mAP50 by 37%.

Table 3
Use case model metrics results

Iteration	Model	mAP50	mAP50-95
1st iteration	YOLOv8n	0.27	0.12

2nd iteration	YOLOv8n	0.37	0.16

Once the training results of the customized YOLOv8nano model have been theoretically evaluated, its performance is assessed in an industrial production environment by inferencing images collected and never used in the training process. By evaluating the prediction results, the class anomaly, bounding box region, and confidence level can be observed, and all provide information on how specific the algorithm is to the provided prediction. For the proposed use case, inclusions are easily detected by the YOLOv8 model (Figure 2).

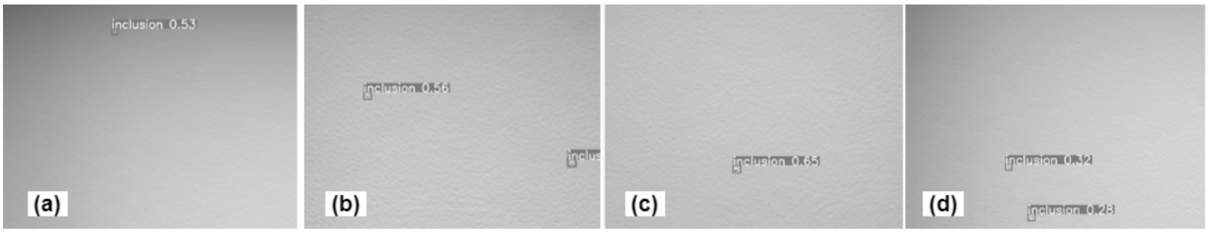

Figure 2 Inclusion detection on unseen data with 2nd model iteration.

The results from the current AI algorithm are based on the neural network and trained with a dataset of 290 images, and the inclusion detection defect (Figure 1A) in the painting process is easily detected. The current trained algorithm allows the identification of inclusion anomalies, but it cannot correctly identify the remaining anomaly classes due to the low dataset employed. Further action will include the dataset augmentation with new high-quality data and improve the detection capabilities on the non-inclusion classes.

4. Conclusions

1. In this paper, it has been developed an artificial vision system to implement automatic inspection of painted surfaces of windmill towers. The model has proven good performance (0.37 mAP50) in detecting inclusions, the most common defect of the use case. Promising results in the aiming fully automating the task and reducing waste. Challenge of data collection and maintenance of production machine learning models. It is essential to consider that data collection for model training is a recurring task that must be carried out periodically to adapt our model to new types of defects and to balance the dataset so that all classes of anomalies are correctly represented. Increasing the number of annotated anomalies in the dataset contributes to the model's enhanced ability to detect and classify anomalies in diverse scenarios, including different lighting conditions, and ultimately improves the deployed solution's reliability and effectiveness. As future work, it is planned to extend the dataset samples to properly cover other types of defects.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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