Leveraging explainable Artificial Intelligence for real-time detection of tidal blade damage

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Abstract—**Fossil fuels are the main cause of global warming and threaten our survival. Tidal turbines can supply renewable energy and fight climate change. Whereas large scale of installation will lower the levelized cost of tidal energy to EUR100/MWh, making ocean energy competitive with other renewable energy sources like offshore wind. To achieve the target, increased performance and reliability of tidal energy devices are required. Tidal turbine blades are one of the primary component of tidal turbines, and can experience complex non-linear damage modes. Tidal blades can fail catastrophically due to impact damage, delamination, matrix crack, fibre breakage or rupture, and others in harsh marine environments. Thus, tidal energy companies must ensure blade health and performance. In the sea, fault diagnosis and maintenance are difficult, and if left unattended, the tidal energy system may fail. Therefore, we proposed real-time and reliable structure health monitoring (SHM) tidal blades. We addressed the trustworthiness of system decisions made with explainable artificial intelligence (XAI), which is recommended approach by EU for utilization of AI. This paper presents a real-time damage detection framework, ICT-based infrastructure for real-time monitoring, and a novel model to classify/detect blade structure damages. Testing and evaluation of proposed approach in laboratory and operational settings is the future concern of this study.**

Keywords—**tidal energy turbines, structure health monitoring, explainable artificial intelligence.**

I. INTRODUCTION

GLOBAL warming is a concern as the earth's temperature rises 0.08°C per decade [1]. Fossil fuels are a major contributor to global warming and threaten our survival. For years, engineers and scientists have studied alternative electricity generation methods to reduce CO2 emissions [2]. Renewable energy is eco-friendly and accessible [3]. Thus, renewable energy solutions and cost-effective, reliable clean energy must be prioritized [4]. Tidal energy turbines can help meet global clean energy and climate needs. Europe leads tidal energy with 30 MW installed by 2020 [5]. Due to the harsh operating environment, tidal energy system rotors and blades might degrade and fail. The Sustainable and Resilient Structures research group at University of Galway uses finite-element analysis and computational fluid dynamics to improve tidal turbine blade design. Other research groups are optimizing tidal blade structures and control technology ([6][7]). (e.g. [8]). A large-scale structural testing of tidal turbine blades and components in recent years to ensure blade structural integrity before deployment. A 3/8th-scale blade component and rotor portion for the Open-Hydro prototype tidal turbine were fatigue-tested in 2017 [9]. In 2020, a static and cyclical testing program was completed on a helical foil for tidal turbines [10] and an advanced structural testing program on a full-scale blade for the Orbital Marine Power tidal turbine, which included fatigue cycles for 20 years of operation. The latter was static-tested at about 1,000 kN [11]. Other studies have created and performed laboratory accelerated life testing on the tidal turbine's generator shaft and support structure to measure fatigue performance [12]. Design techniques and full-scale laboratory testing are helping enhance tidal turbine rotor and blade reliability and efficiency. Tidal energy is slowly developing compared to other renewables.

Most previous research works have concentrated on optimizing tidal turbine designs [13][14], although component health monitoring is essential for reliable operations. Wind turbine structure health monitoring is

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well-established [15]. Despite design similarities, tidal and wind power turbines operate in different environments [16]. Tidal energy turbines cannot employ most wind turbine SHM methods. Tidal energy turbine SHM has been studied recently. A research [17] emphasizes the requirement for SHM to detect damage during tidal turbine operation, including misalignment, imbalance, looseness, broken gear teeth, bearing problems, lubrication fluctuation, dry contact with spinning surfaces, and excessive wear. Some researchers already tested their technologies in the field (for example [18]). A recent study proposes predictive monitoring for subsea power producers (permanent magnet synchronous generators) to minimize the chance of catastrophic failure [19]. This study focuses on tidal generator SHM. Many of the fractures that can contribute to tidal blade structure deterioration have been experienced and reported from tidal energy devices deployed in real sea conditions, such as connection failures, water ingress reducing fatigue life, blade edge erosion, biofouling, and higher blade loads than expected. Tidal turbine performance, dependability, availability, maintainability, and/or survivability have decreased. Existing real-time SHM methods also ignore key factors. Thus, there is an urgent need to design and implement quick, reliable, and robust real-time SHM systems on both new blades going into the sea and equipment on existing turbines to improve reliability and performance over the whole tidal turbine life in complicated ambient tidal circumstances. To receive real-time information, you also need a solid ICT infrastructure, and ensuring the trustfulness ot system responses such as inclosure of sensor systems to be employed in real-time for monitoring the material state of composite materials, as well as sensor data dependability, creating a massive cloud-based composite materials database that includes all material characteristics SHM and prognostics data. Also, it is necessary to build data-driven adaptive AI models to detect damages, as well as continuous learning methods to forecast unknown breakdown events. To speed up the process, integrate data-driven AI models with transfer learning and multi-task learning techniques can also be useful. Additionally, ensurance the trustworthiness is an essential element, for that reason a novel method, which could ensure the reliability and trustworthiness of the system's decision, such as informing the user about the rationale of the black-box decision provided by the system is mandatory. The primary concern is transparency to the results, where state-of-the-art XAI techniques, for example, transparent model, model-specific explanations, and existing composite material failure theories to develop explanation criteria of several structure conditions of the tidal blade. The explanation of the decision are defined using the interpretability approaches such as visual, text, or numerical modeling feedback.

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II. Proposed Technology

This framework collects real-time data to identify tidal blade health patterns using ML. The structure features and crucial factors will be used to comprehend these patterns and annotate the data with specific tidal blade health problems, which will be utilized as the training dataset to construct the data-driven (using the right approach for damage detection) method. Using a comparative study over a variety of ML and outliers to efficiently identify structural damage is the purpose of statistical and ML-based analysis. Those indications will help identify and analyze the damage. Composite mechanics theory and numerical calculation can be used to model exterior impact damage. Numerical simulations create monitoring data to characterize structural damage. ML algorithms intelligently find tidal blade construction damage in the monitoring data. Training and testing the network with structural data such as modal frequencies, shape, strain energy can be used to localize and determine the extent of the damage. Damage alters structural stiffness and dynamic characteristics, revealing the most important elements. Comparing structural dynamic data to reference values helps reveal and repair tidal blade structure damage. This innovative tidal blade approach will help industrial decision-makers evaluate blade microstructure health issues (including delamination, debonding, cracking, strain level, and others). XAI was employed to build the white-box decision technique (increase system confidence).

2.1 Sensor Technology and Real-time Data Acquisition Process

This project will require extensive analysis of the tidal blade performance and fatigue testing data (available at hosting institute-NUIG, Structure Lab) to identify the structural damage pattern and features that contribute to the deterioration of the material. For the monitoring and system validation purpose, new data will be acquired using the sensor technology. Therefore, the data quality checks during data acquisition and processing will be essential. Data completeness, reliability parameters, types, data formats must follow the specification. Also, the quality check during and after collection, data should be analyzed to verify consistency, reasonable distribution, code compliance, and correct interpretation according to planning measures. Monitoring of the tidal blade health condition is an essential component of this study. Typically, waterproof/ underwater sensor and bonded sensor patches will be required to determine the structural properties of the tidal blades. Some of the available options could be a strain sensor patch designed to conform to the structure's shape. Further, some vibration and acoustic sensors could be helpful to determine the factors and impact of damage or fractures which lead to cracking and pitch system failure. Whereas to determine the recommended number of sensors for each tidal blade and their configuration will be optimized. Sensors that monitor parameters required for condition assessment and monitoring, such as determining physical changes incurred during operations, are the main components of the SHM system. Cracks, erosion, fiber structural deterioration, and other issues are examples. The decision of which intervention to use is based on the analysis of the sensor data that is being monitored. During the functioning of tidal energy turbines, sensors can be positioned inside or outside the tidal blades, or in the form of collected photographs. As a result, it must be exposed to regular health checks. According to the data obtained from the sensors, the sensors take action. For example, for real-time monitoring of tidal blade curing based on sensor input (optical, acoustic, or image).

2.2 LoRaWAN-based Gateways, Network Communication Protocols, and Microservices

The LoRaWAN protocol is a low-power wide-area networking standard. Designed to connect battery-operated devices to the internet via wireless connections in regional, national, and worldwide networks. LoRaWAN defines the network's communication protocol and system architecture using the ISM bands, while the LoRa physical layer establishes long-range communication links between remote sensors and gateways linked to the network. It is well suited for delivering tidal energy because it is low-power and has a long-range of up to 10 to 15 miles. Marine settings are particularly hostile, making it difficult to maintain equipment installed overboard or to measure environmental parameters. Because of their robustness to interference, which naturally occurs in a marine environment, LoRa modulation and the LoRaWAN protocol proved to be suitable solutions among all the enabling technologies. However, LoRa-based complete network infrastructures for deployment offshore, as well as LoRa transmissions across seawater in general, are still active research areas today, resulting in a literature gap. As a result, Sensor Nodes transmit encrypted LoRa packets using a frequency hopping strategy as specified by the LoRaWAN standard. Ashore, two LoRaWAN Gateways are installed, which are in charge of demodulating the signals and transmitting the received data to a distant server via the Message Queue Telemetry Transport protocol. The Server is responsible for dealing with incoming packets: once they have been appropriately received and modified to extract any usable data, the Server makes them available to users by storing them in a database and providing a graphical interface. The microservices will follow the Microservice Oriented

Architecture and be deployed over the AWS container (under the Amazon Elastic Compute Cloud, as shown in Figure 1). For each microservice, they will be a dedicated container in the cloud. As shown in Figure 2, the data repository (AWS DynamoDB) will communicate with each microservices. Also, separate data stores will be formed from the database to follow the microservices design pattern. A single system will be built by the combination of several individual microservices. The microservice-based architecture will be essential to build scalable, large, and complex applications. Along with scalability, it also ensures easy to build, update, deploy and simplify real-time processing. One of the best open-source options to build a microservice is the Python programming language. Because the microservices will be employed with the trained AI models, therefore Python is more desirable (provides a wide range of libraries, such as Numpy, Pandas, TensorFlow, Scikit Learn, Seaborn, and others). Besides Python, other options are available, such as Java, PHP, and others. A microservice API gateway interfaces between the microservices and other user applications (web-based and mobile-based applications). It accepts all application programming interface (API) calls, aggregates the various services required to fulfill them, and returns the appropriate results.

2.3 *Security and Privacy Preservation*

Data confidentiality, data integrity, data availability, data encryption, infrastructure security, configuration management, identity and access control, monitoring and logging, and multiple account access are some critical features that the system must provide to secure cloud infrastructure and allow customers to safeguard their workloads. In the proposed infrastructure, a variety of security and privacy preservation tools has been suggested using the amazon cloud.

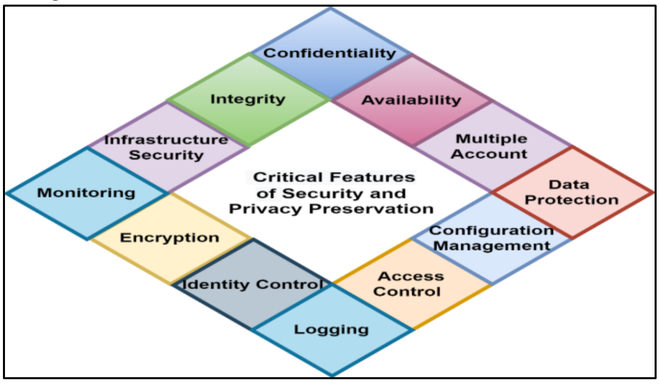

Figure 1: Security and Privacy Preservation for SHM System of Tidal Blades

2.4 *Cloud Computing Platform*

The anticipated ICT infrastructure makes use of hybrid cloud computing services, which are a combination of private fog and public cloud computing. On the one hand, it facilitates data access via the Internet to anywhere in the world and provides an elastic environment when dealing with a rapidly increasing flow of data and calculation resource demand, such as damage occurrence over the tidal blade surface or the supervisor's request for current condition details. On the other side, due of the reduced need for storage, large computational resources could be saved. This is because raw data preprocessing, such as data cleansing and duplication, as well as the training of complicated digital models, is done first in a private environment. Although the cloud platform is adaptable and scalable, there are some limitations to consider when implementing the system. To commence, compute resources must be assigned a priority to avoid potential user authentication conflicts. The detail of the infrastructure in mentioned in Figure 2. For the implementation purpose, the LoRaWAN based supported technologies (sensors, gateway, protocol, and others) will be integrated with Amazon Web Services Infrastructure and services (as shown in Figure 2). Such as Amazon Elastic Computer Cloud (IaaS), AWS IoT Core, AWS Dynamo DB, Amazon Machine Learning and Amazon Kinesis. Installed sensors over the surface of tidal blades record and send data (acoustic/ optical strength/ physical structure images or other) via LoRa radio frequency modulation to Gateways. The LoRaWAN based gateway uses GSM to transmit the data the to AWS network server. Later, using the MQTT/ AWS integration,

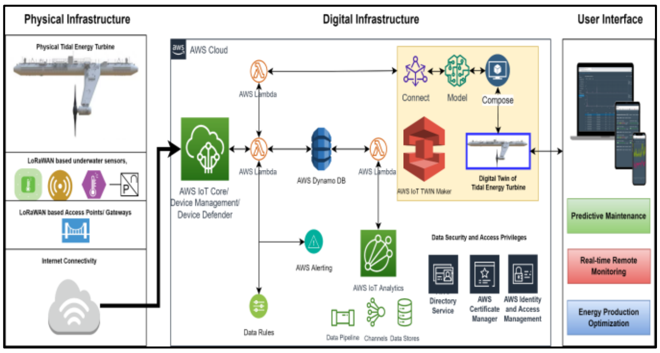

Figure 2: Proposed AWS based Cloud Infrastructure for SHM of Tidal Blades

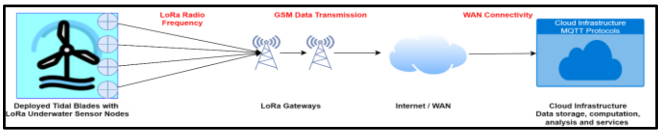

Figure 3: Data Transmission Protocols and Connectivity

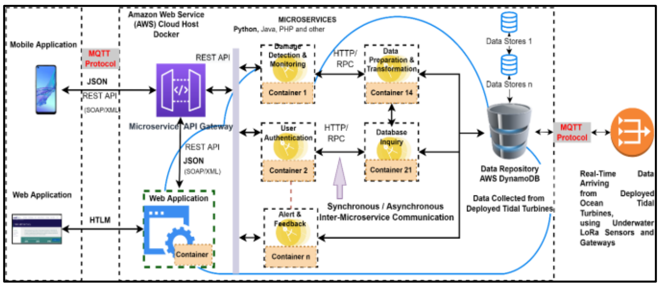

Figure 4: Cloud based Microservices for SHM of Tidal Blades

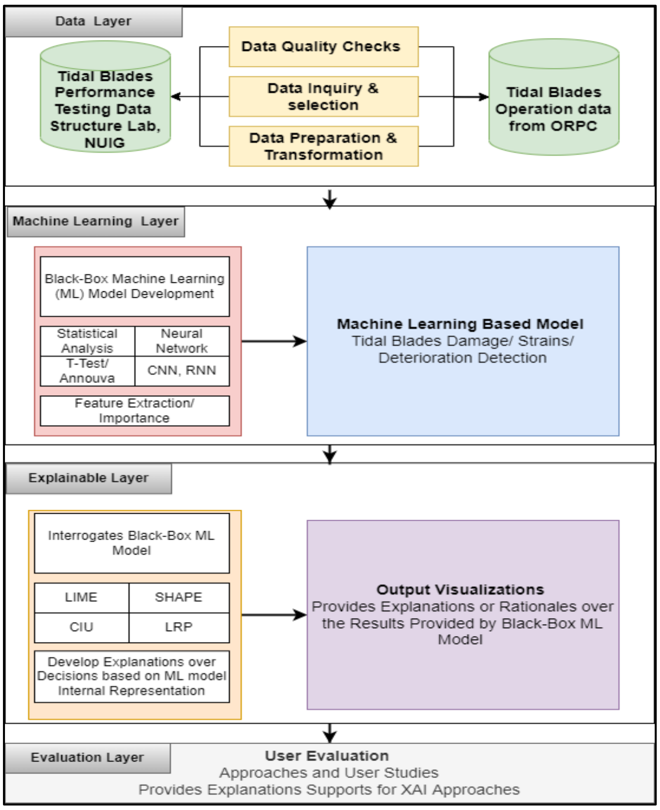

Figure 5: XAI based SHM approach

The network server communicates with AWS IoT core to transfer data, which is put into the AWS DynamoDB database using the lambda functions of AWS. In addition, the AWS rules engine will be responsible for reporting if collected data is against the defined data rules. Also, ocean and weather environment data will be connected with the database to collect the ocean and weather conditions of that region. Also, survey-based data collection will be done to collect non-sensor-based data. Once sufficient data has been collected, data analysis and machine learning tasks will be performed to identify the correlations among the critical factors of damage detection, and know deterioration and possible future damage patterns. For that purpose, Amazon Kinesis and Machine Learning packages will be used. Also, the microservices will be developed to translate those findings and integrate them for users using web-based and mobile applications, as shown in Figure 2. Figure 3 displays the overall system architectural design, which demonstrates how the SHM system would execute monitoring. Amazon's Elastic Block Store, Simple Storage Service, Relational Database Service, and Redshift all include built-in encryption. Server-Side Encryption with S3-Managed Keys, SSE with AWS KMS-Managed Keys or with Customer-Provided Encryption Keys are all options for AWS Key Management Service. Built-in VPC network firewalls with private or dedicated on- or off-premises connectivity choices, layer 3, 4, or 7 distributed denial of server mitigation technologies, and automated traffic encryption between all AWS facilities — global and regional — are available for infrastructure security. Configuration management tools were used to create or shut down AWS resources, manage changes, obtain an inventory of cloud assets, replicate tested secure configurations using infrastructure as code templates, and create standard, preconfigured, hardened virtual machines using Amazon Machine Images. Allow Identity and access control to define, enforce, and manage user access policies and access to cloud resources, service APIs, and the Amazon Console. User accounts and roles are defined using AWS Identity management. Multi-Factor Authentication and Single Sign-On provide secure login options. Cloud Trails keep track of the AWS cloud environment, including any API calls or console operations, to keep and logging. Amazon CloudWatch collects standardized log data from all Amazon services, and Amazon GuardDuty analyzes logs in real-time to detect fraudulent or illegal activity. Adding the Several Accounts AWS Control Tower to a customer's account makes it easier to set up and manage multiple accounts and teams. As depicted in the below picture, the Security Perspective approaches security themes as Scrum epics with several sprints addressing a variety of user stories, including both use and misuse situations. This method enables rapid iteration and maturation of security features on AWS while keeping the flexibility to respond to changing business needs.

Figure 5, the hypothetical SHM system will consist of four layers. Data pre-treatment quality control, and transformation will be conducted in the data layers. Tidal Health Structure database (from sensors) is important for system validation, while the Performance Testing database mostly helps with model building. The next layer is the machine learning layer, which receives the data as input and generates a classification output (black box) for damage detection. Afterwards, the explainable layers use the XAI algorithms (LIME, SHAP, and others) and explain the findings through graphical reports. Over the explainable layer lies the assessment layer, which gives psychological or meaningful explanations.

2.5 *Details of explainable AI for tidal blade detection*

An explanation text variable with a damage description generates a XAI explanation in the procedure below. Use case-specific text may be added. The explanation, original picture, predicted class, heatmap, and overlay image are presented together to provide the XAI explanation for damage identification in tidal blade images.

ALGORITHM FOR DEVELOPING EXPLANATIONS

[STEP 1] Load the pre-trained model for damage detection in tidal blades: model = load_model('damage_detection_model.h5').

[STEP 2] Load an example tidal blade image: img = load_image('tidal_blade_image.jpg').

[STEP 3] Preprocess the image by resizing and applying necessary transformations: preprocessed_img = preprocess_image(img).

[STEP 4] Generate predictions using the pre-trained model: predictions = model.predict(preprocessed_img).
[STEP 5] Decode the predictions to obtain the top predicted classes and their corresponding probabilities: decoded_predictions = decode_predictions(predictions).
[STEP 6] Get the index of the predicted class with the highest probability: predicted_class_index = argmax(predictions).
[STEP 7] Retrieve the output tensor of the last convolutional layer in the model: last_conv_layer_output = model.get_layer_output('last_conv_layer').
[STEP 8] Create a gradient model to compute the gradients of the predicted class with respect to the output feature map of the last convolutional layer: grad_model = create_gradient_model(model, last_conv_layer_output).
[STEP 9] Compute the gradients using a gradient tape and the predicted class index: gradients = compute_gradients(grad_model, preprocessed_img, predicted_class_index).
[STEP 10] Pool the gradients over all the channels to obtain the importance scores: pooled_gradients = pool_gradients(gradients).
[STEP 11] Retrieve the output value of the last convolutional layer for the input image: last_conv_layer_output_value = get_last_conv_layer_output(preprocessed_img).
[STEP 12] Multiply each channel in the feature map array by the corresponding gradient importance score to obtain the heatmap: heatmap = compute_heatmap(last_conv_layer_output_value, pooled_gradients).
[STEP 13] Normalize the heatmap values between 0 and 1: normalized_heatmap = normalize_heatmap(heatmap).
[STEP 14] Resize the heatmap to the original image size: resized_heatmap = resize_heatmap(normalized_heatmap, img_size).
[STEP 15] Apply a color map to the heatmap for better visualization: colored_heatmap = apply_color_map(resized_heatmap).
[STEP 16] Superimpose the heatmap on the original image to highlight the regions of interest: superimposed_image = superimpose_heatmap(img, colored_heatmap).
[STEP 17] Generate an XAI explanation text based on the highlighted regions: explanation_text = generate_explanation(colored_heatmap).
[STEP 18] Display the original image, predicted class, heatmap, superimposed image, and the generated explanation text: display_results(img, decoded_predictions, colored_heatmap, superimposed_image, explanation_text).

1. Input Explanations: In tidal blade damage detection, input explanations try to show how certain areas or characteristics in the photos affect the model's decision-making process. The XAI approach analyzes picture data and creates visualizations or relevance ratings that emphasize the blade sections most significant for identifying defects or fractures. These explanations may assist users comprehend the model's decision-making areas.
2. Output explanations: Output explanations describe why the model decided to include or exclude fractures or defects in the tidal blade picture. The XAI technique evaluates the model's internal workings and discovers key traits or patterns that affected the conclusion. It visualizes or describes the important criteria or evidence utilized by the model to identify damages. These explanations may assist users comprehend the model's predictions.
3. Techniques and graphics: The XAI approach used to identify deterioration in tidal blades may use numerous techniques and graphics to explain. It might employ saliency maps or heatmaps to emphasize the visual parts that greatly influence the choice. These visualizations may help users understand which elements of the tidal blade picture are causing the model to identify faults or fractures.
4. Interpretability and user knowledge: The provided explanations seek to improve interpretability and user knowledge of the model's damage detection judgments in tidal blades. The explanations assist users understand the model's elements by clearly visualizing or describing key areas or characteristics. They allow users to assess and understand the model's detection process, increasing trust and confidence in the model's accuracy and efficacy.
5. Integration with model outputs: The model's predictions are used to produce explanations. After the model discovers fractures or defects in a tidal blade picture, the XAI approach analyzes the decision process. The model's explanations provide context and rationale for the discovered faults or fissures.
6. Application specific considerations: Tidal blade damage detection explanations should be adjusted to the blades' features and forms of damage. For instance, the explanations might concentrate on blade sections prone to deterioration, fracture patterns, or structural aspects that affect detection. This adjustment makes the explanations relevant and useful for tidal blade examination.

III. CONCLUSION

Despite the optimal design of tidal turbines, it is vital to check the health of turbine components to ensure reliable operation and catastrophic failure. Tidal blades are key components of tidal turbines that are subject to performance degradation due to the harsh operating environment, which could result in serious performance failure or breakdown if left unattended. Therefore, to address this issue, in this paper we have proposed framework consisting of state-of-art information communication technology, including sensor/ devices, cloud technology, equipped with responsible or trustworthy artificial intelligence (called as explainable AI). Initially, a real-time technological infrastructure is proposed with ensuring the security and privacy under consideration. Later, we have suggested some amazon web service based technologies can be used to develop this framework. Our core framework at software level is divided into three different layers, data layer, machine learning layer and explainable artificial intelligence (XAI) layer. We have also proposed a algorithm for XAI layer, which is novel step for this technology, which ensures the transparency in the black box decisions made my machine learning models (ML). In future study, model hyper-parameters will be optimized using critical components and tidal blade deterioration patterns and more critical explanations will be addressed to detect the structure health. The most significant part of XAI is comprehending psychological or meaningful explanations through domain-specific criteria development, but the tidal blade has no such criteria, thus in future, it is more crucial for researcher to contribute in this direction. The proposed solution in this paper open the way to further improve this technology and contribute in the direction to develop predictive approach for tidal blade monitoring and damage detection, which is also the future concern of this study.

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