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INTEGRATED HARDWARE–SOFTWARE COMPLEX FOR WIND TURBINE BLADE DEFECT CLASSIFICATION

The **subject matter** of this article is an integrated hardware–software complex for real-time detection and classification of wind turbine blade defects using an unmanned aerial vehicle (UAV) equipped with onboard edge-AI modules. The **goal** of the study is to develop and experimentally validate an autonomous embedded framework capable of collecting, processing, and interpreting blade-surface image data under field conditions while maintaining sufficient diagnostic accuracy and real-time performance on resource-constrained hardware. The **tasks** of the study are to design the architecture of the UAV-based inspection system; to implement an onboard processing pipeline including image acquisition, preprocessing, defect detection, classification, and georeferenced data association; to develop a lightweight YOLO-based visual detection stage combined with a neuro-fuzzy decision module; and to evaluate the diagnostic and computational performance of the proposed system on Raspberry Pi 5. The methods used include lightweight deep-learning-based visual analysis, neuro-fuzzy inference based on Gaussian membership functions and Wang–Mendel-type adaptation, telemetry-assisted defect georeferencing, and experimental evaluation under embedded deployment constraints. The **results** obtained show that the developed prototype provides stable onboard operation at 5–6 FPS for 640×480 video, supports local processing without cloud infrastructure, and ensures reliable defect-state recognition for four predefined blade-surface classes: Erosion, Corrosion, Crack, and Pristine. In the integrated validation workflow, the system achieved 88.1% classification accuracy, while the neuro-fuzzy decision module evaluated separately on YOLO-derived class-coefficient vectors achieved 94.0% accuracy with an MSE of 0.0686. **Conclusions.** The scientific novelty lies in the development of a fully autonomous UAV-based diagnostic architecture that combines onboard visual detection, telemetry fusion, and neuro-fuzzy decision support on limited embedded hardware, as well as in the adaptation of the neuro-fuzzy classifier for real-time multiclass blade-condition assessment.

Keywords: wind turbine blades; UAV inspection; defect detection; deep learning; neuro-fuzzy system; edge-AI; YOLO; Raspberry Pi.

1. Introduction

1.1. Motivation

The development of a wind turbine blade defect-detection system using an unmanned aerial vehicle (UAV) aims to improve the efficiency and safety of wind farm condition monitoring. The system should enable autonomous flight over turbines, capture real-time images of blades, and automatically detect defects without operator intervention during flight. The UAV, equipped with a camera and a Raspberry Pi computing module, collects images that are then analyzed by built-in artificial intelligence algorithms. This approach enables the detection of defects at early stages of turbine operation, significantly reducing maintenance costs and increasing system reliability.

The algorithmic core of the system combines a convolutional neural network (CNN) for extracting

feature vectors from each frame and a neuro-fuzzy system (NFS) for classifying the blades' state. The CNN extracts compact visual feature representations from the input images and provides class-related confidence estimates for the detected blade regions. The latter determines the defect class or confirms the blade's normal state. In case of detection of damage, the system generates a message indicating the type of defect, the coordinates of its detection, the level of confidence of the neural network and transmits data to the operator via a telemetry communication channel.

The system should operate in real time, providing frame processing at a speed of at least 4–6 FPS and classification accuracy of at least 85%. For this purpose, optimized lightweight CNN architectures (e.g., YOLO, SqueezeNet) are provided, as well as an adaptive neuro-fuzzy classifier implemented directly on Raspberry Pi 5. The input data are images of the blades and telemetry information (GPS coordinates, altitude, drone



orientation), and the output data are defect classes, confidence levels, evidence images, and status reports of the wind turbine.

Therefore, the goal of this study is to develop and experimentally validate an integrated UAV-based hardware–software complex for real-time wind turbine blade defect detection and classification on resource-constrained embedded hardware. The achievement of this goal is assessed using three groups of indicators: diagnostic performance of defect recognition, computational efficiency of onboard processing, and operational autonomy enabled by local inference, telemetry synchronization, and onboard data storage.

1.2. State of the arts

The rapid growth of wind power capacity, the increase in the number of wind farms and the transition to digital principles of energy infrastructure maintenance determine the need for the creation of intelligent mobile monitoring systems capable of ensuring early and highly accurate detection of damage to wind turbine blades. Turbine blades are exposed to complex wind, mechanical, and weather factors, which lead to the appearance of various defects, including edge erosion, cracks, delamination of composite layers, corrosion, local fatigue damage, and impact deformations. Early diagnosis of such defects is critically important, since undetected damage can enter the uncontrolled development phase, cause increased vibrations, rotor imbalance, a significant decrease in efficiency, and, in the worst case, blade destruction. Traditional inspection methods, in particular ground or rope inspections, require stopping the turbine, involve high-altitude specialists and specialized equipment, and significantly increase costs and create additional risks. This makes automated UAV-based diagnostic systems one of the most critical areas of modern research.

The literature confirms the industry's transition from static visual inspection to data-driven monitoring concepts based on deep neural networks, multimodal sensor systems, and autonomous unmanned platforms. A review of current trends in wind turbine monitoring shows the widespread adoption of high-precision image analysis techniques and the development of digital twins of wind turbines, which is significantly changing the maintenance paradigm [1]. Research shows that modern turbines are increasingly viewed as cyber-physical systems, the condition of which can be assessed using autonomous inspection platforms integrated with predictive analytics, big data analytics, and risk assessment models.

In this context, mobile systems based on unmanned aerial vehicles have become widespread, as they enable inspection without stopping the turbine, operate at high

altitudes and under challenging conditions, and provide the opportunity to obtain detailed, georeferenced images of the blades. A detailed examination of recent scientific literature highlights a rapid evolution of UAV-based diagnostic technologies for wind turbine blade inspection, particularly those integrating deep learning, multimodal sensing, and onboard edge-AI platforms. The work [2] provides one of the most comprehensive overviews of current inspection methodologies, emphasizing the paradigm shift from manual and rope-access inspections toward autonomous unmanned systems capable of high-resolution imaging and intelligent defect interpretation. Importantly, the review stresses the increasing relevance of onboard embedded computing and lightweight convolutional neural networks, noting that real-time inference directly on UAV platforms represents the next evolutionary step in field diagnostics. This aligns directly with the architecture proposed in the present article, which implements a lightweight CNN–neuro-fuzzy hybrid model on a Raspberry Pi 5 for real-time classification under strict computational constraints.

Further refinement of UAV-based approaches is presented in [3], who examine inspection of both static and rotating blades - a topic particularly relevant to the proposed system because rotational motion introduces significant geometric and illumination variability during data capture. The authors highlight the lack of large annotated datasets and the need for hybrid models capable of improving interpretability directly addressed by the neuro-fuzzy subsystem developed in the paper.

A complementary perspective is offered by authors of [4], who analyze the advantages and limitations of fully UAV-assisted damage detection and highlight the transition toward "intelligent mobile inspection ecosystems." Their review underscores that the reliability of UAV-based diagnostics depends not only on neural model accuracy but also on real-time processing capability, communication resilience, and flight-path optimization. The authors make a strong argument for using lightweight deep learning models and platform-level optimization (quantization, pruning, tensor acceleration), reinforcing the methodological choices of the present study, where INT8-optimized CNNs are deployed on embedded hardware. Their findings also confirm the importance of integrating telemetry information to refine detection coordinates, which is implemented in our system through synchronized sensory fusion of RGB, GPS, IMU, and LIDAR data.

From a technological standpoint, [5] provides a focused review of drone-based inspection technologies, discussing camera stabilization systems, sensor configurations, gimbal architectures, and communications frameworks. Their analysis highlights that many existing UAV inspection systems rely heavily

on external servers or cloud processing, which introduces latency and limits autonomous operation. This observation underscores the novelty of the system described in the article, which performs *all* detection, classification, and georeferencing directly on the UAV through on-board computing. Although the authors of [6] examine a domain outside of wind turbine inspection. Their work demonstrates the effectiveness of neuro-fuzzy models for real-time, safety-critical tasks on embedded platforms with limited computational resources. It also illustrates how fuzzy rules combined with neural adaptation can enhance stability, interpretability, and resistance to dynamic disturbances.

It is necessary to note that, unlike ground-based telescopic systems [7], drones offer greater positioning flexibility, the ability to orient the object at different angles, and the ability to respond quickly to changes in spatial geometry and blade orientation.

An important area of research is the application of deep learning for automatic damage detection and classification. The literature demonstrates a significant dominance of convolutional neural networks (CNN) in architectures used for blade surface analysis. Lightweight CNN models, developed based on the principles of mobile architectures, such as MobileNet, ShuffleNet, or SqueezeNet, provide efficient operation on computationally limited platforms, including Raspberry Pi and other single-board computers [8]. Up-and-coming solutions use attention mechanisms to localize minor defects, such as microcracks or erosion patterns [9], and cascade models that first perform inclusion localization and then their detailed classification [10]. For crack detection tasks, architectures that operate on spectrograms or texture derivatives have been proposed, enabling increased sensitivity to very subtle structural changes [11].

Despite significant progress in deep learning, many works emphasize the importance of fuzzy and hybrid architectures to ensure robustness to changes in illumination, noise, and partial surface overlaps [12, 13]. Authors [14] proposed a learning-rate estimation technique that ensures stable and accelerated convergence of MLP models under non-stationary data conditions. Their findings are relevant for systems requiring reliable gradient adaptation, particularly for the neuro-fuzzy classifier in our architecture, where stable real-time weight updates are essential. Authors [15] introduced a deep neural network with adaptive PReLU activations and fast learning, improving accuracy and convergence speed on heterogeneous data. This approach demonstrates the efficiency of adaptive mechanisms in resource-constrained environments, aligning with the need for rapid defect classification on onboard edge-AI modules.

The combination of CNN and neuro-fuzzy methods

allows for reconciling high recognition accuracy with the interpretability of decision parameters. In works devoted to hybrid systems, it is proposed to combine feature vectors generated by CNN or YOLO-like models with fuzzy rules of the "if-then" type, which allows for compensating for uncertainty in the case of close values of class probabilities, as well as to ensure adaptability to new types of defects [16,17]. Approaches that combine fuzzy logic with image analysis also demonstrate high efficiency in the critical assessment of blade condition, when it is crucial not only to detect damage but also to assess its impact on turbine operation.

Work focused on creating integrated systems that perform the full inspection cycle, from UAV data collection to analysis on the edge platform and transmission of the final results to the operator, is becoming increasingly important. Some studies are devoted to architectures that work not only with RGB frames but also with multimodal data, including infrared images, depth maps, and LIDAR data, which allow reconstructing the blade's spatial structure and more accurately localizing defects [18,19]. Models are being developed for offshore turbines that account for the risks posed by harsh weather conditions, high equipment loads, and the difficulty of maintaining stable communication [20]. Solutions are also emerging that focus on internal inspection of the blade cavity, where autonomous drone navigation in narrow spaces requires integrating LIDAR, inertial sensors, and computer vision [21].

In parallel, methods for creating digital twins of wind turbine blades are being developed, enabling the prediction of defect development over time and linking detection results to mechanical models of material degradation. In works on digital twins, the importance of high-accuracy georeferencing, the ability to reconstruct the 3D shape of the blade, and the integration of data from different sources into a single model is emphasized [22]. Such approaches open up the possibility of moving to predictive maintenance of wind turbines - that is, predicting how exactly and at what speed a certain damage will progress, which allows optimizing maintenance.

In related areas of renewable energy, such as solar panel diagnostics, UAVs equipped with RGB and thermal imaging cameras are actively used to detect temperature field anomalies and visual defects, laying the groundwork for transferring similar technologies to wind energy [23]. This confirms the universality of deep learning methods for surface defect analysis and underscores the potential to deploy technological solutions across diverse green energy sectors.

A review of the current state of scientific research highlights several significant challenges. First, most deep learning models have substantial computational

requirements and cannot operate in real time on low-power edge devices without considerable optimization. Second, current publications emphasize the lack of extensive, qualitatively annotated datasets from real wind farms, which limits the ability to generalize models and complicates comparisons across methods. Third, the issue of the autonomy of systems that must operate in conditions of unstable communication or a complete absence of cloud infrastructure remains insufficiently studied. Fourth, little attention is paid to the creation of complex architectures that combine defect classification with fuzzy methods of criticality assessment, the construction of a digital twin, and integration with a maintenance planning module.

It is these shortcomings that determine the scientific novelty and relevance of the article, which proposes the architecture of a mobile intelligent system adapted for implementation on board a UAV using Raspberry Pi and an NPU hardware accelerator. The system described in the work combines lightweight CNN models, real-time processing of an RGB stream, georeferencing of detected defects, integration of telemetry data with the camera, neuro-fuzzy classification methods based on feature vectors, and the ability to operate without a cloud infrastructure. Authors [24] present a comprehensive review of deep learning methods for detecting wind turbine blade defects, emphasizing the computational challenges that motivate the use of lightweight models.

In [25], the researchers highlight the role of smart, data-driven non-destructive inspection technologies in Industry 4.0, underscoring the importance of multisensor integration and real-time analytics. [26] demonstrate that classical digital image processing can detect simple surface defects but lacks robustness under complex conditions, reinforcing the advantages of deep-learning-based detection. Authors [27-29] compare deep learning models for drone inspections and show significant performance variation across architectures, supporting the use of optimized YOLO variants on embedded hardware. Researches of [30, 31] validate the effectiveness of neural networks for diagnosing structural anomalies in rotating composite blades, illustrating the broader applicability of AI-based inspection approaches.

Authors [30] demonstrate that accurate defect detection is achievable even on low-cost drone platforms, aligning with the resource-efficient design of our Raspberry Pi-based solution. Finally, [32] shows that AI-based image analytics significantly outperform traditional techniques for crack and damage detection, supporting the integration of deep learning into the hybrid detection-classification pipeline used in our architecture.

Thus, the literature review demonstrates that although there is a wide range of methods and systems for wind turbine blade defect analysis, none of the

existing developments provide a simultaneous combination of autonomy, mobility, low power consumption, real-time operation, fuzzy criticality logic, and full integration with UAV onboard equipment. This justifies the need to develop the architecture presented in the article, which combines the best practices of computer vision, fuzzy modeling, and mobile platforms to increase the efficiency and reliability of modern wind turbine monitoring systems.

1.3. A goal and tasks

A goal of this paper is to develop and validate a mobile intelligent system capable of autonomously detecting and classifying the wind turbine blade defects in real time using data acquired by an unmanned aerial vehicle (UAV). The proposed system is intended to provide reliable defect recognition under embedded deployment constraints, ensure local operation without mandatory cloud support, and maintain sufficient computational efficiency for onboard execution on Raspberry Pi 5. In this context, the study focuses not only on architectural development but also on the experimental confirmation of diagnostic performance, real-time suitability, and operational autonomy.

To reach the set goal, it is necessary to solve the following tasks:

1. Development of the architecture of a mobile detection system: create a structural diagram of the system that includes data collection modules (UAV with camera and sensors), pre-processing, defect detection, classification, result saving, and report transmission to the operator.

2. Development of the algorithmic core: to implement a lightweight YOLO-based model for blade-region defect detection and preliminary visual categorization, and to develop a neuro-fuzzy decision module for final classification of four predefined blade-surface states: Erosion, Corrosion, Crack, and Pristine.

3. Implementing algorithms on limited computing resources (edge-AI): optimize models for inference on embedded Raspberry Pi5 platforms, ensuring performance of at least 4–6 FPS and classification accuracy.

4. Development of integration mechanisms with UAVs: implement an interaction interface between the computing module and flight control systems (GPS, IMU, telemetry) to link defect detection results to spatial coordinates.

The successful completion of these tasks is evaluated using both diagnostic and computational metrics, including classification accuracy, error level of the neuro-fuzzy output layer, frame processing rate (FPS), execution time per decision cycle, and the practical ability of the system to operate onboard without

external computing infrastructure.

The paper is structured as follows. Section 1 provides an overview of current research and methods for monitoring the defects of wind turbine blades.

Section 2 describes the system architecture, data acquisition workflow, and applied algorithms, including the UAV onboard subsystem, the CNN-based defect detection module, the neuro-fuzzy classification model, and the complete real-time processing pipeline implemented on Raspberry Pi 5.

Section 3 presents the results of experimental studies, including real-time performance metrics, accuracy evaluation, stability analysis of the hybrid YOLO–neuro-fuzzy model, comparative analysis with existing prototypes, and discussion of system limitations and practical applicability.

Finally, Section 4 summarizes the conclusions of the work and outlines future research directions, including the extension of the system with multispectral sensing, improved georeferencing, adaptive mission planning, and further refinement of the neuro-fuzzy classifier for real-time UAV-based diagnostics.

2. Materials and Methods of Research

2.1 Structure of the system

The system for the current analysis of the condition of wind turbine blades is designed for autonomous monitoring and diagnosis of damage that can reduce efficiency or pose accident risks. Such defects include cracks, edge erosion, coating delamination, mechanical deformations and corrosion. The system is based on the use of an unmanned aerial vehicle (UAV), which flies around the turbine, captures images of the blades and conducts their intelligent analysis in real time.

From the diagnostic point of view, the wind turbine blade is considered a large-scale composite aerodynamic structure with an external surface accessible to visual inspection. In a simplified representation, the blade includes several functionally significant zones relevant to image-based diagnostics, namely the leading edge, pressure side, suction side, trailing edge, and tip region. Since the proposed system is based on RGB image analysis acquired from a UAV platform, the blade is modeled here as an object with visually observable surface states that can be distinguished under varying viewing angles, illumination conditions, and flight trajectories.

In the present study, the set of target classes is limited to four blade-surface conditions detectable in visible-spectrum imagery: Erosion, Corrosion, Crack, and Pristine. Erosion is interpreted as gradual surface wear, especially near the leading edge, often manifested by roughening, material loss, or coating degradation.

Corrosion is treated as a visually distinguishable surface deterioration pattern associated with local discoloration or damage of the protective layer. Crack corresponds to a localized discontinuity of the blade surface that may develop under cyclic mechanical loading. The Pristine class represents defect-free blade regions. This simplified diagnostic model is consistent with the capabilities of the proposed RGB-based onboard system and does not cover hidden subsurface defects or internal structural degradation not observable in surface images.

The system architecture includes an RGB camera to obtain high-quality images of the blade surface, a laser rangefinder (LIDAR) to measure the distance between the drone and the object, a Raspberry Pi 5 computing module with a neural computing accelerator (NPU), a flight controller, a GPS/IMU module, a power system, and communication channels. The camera is mounted on a stabilized gimbal, which ensures clear images even when the drone is moving. Data from the cameras is synchronized with telemetry and GPS coordinates, enabling you to locate defects accurately.

The onboard computing module performs image pre-processing: stabilization, noise removal, illumination normalization and formation of regions of interest (ROI). Next, a convolutional neural network (CNN) detects defects, and a neuro-fuzzy system (NFS) classifies them by type and degree of damage. Thanks to NPU, calculations are performed at high speed even in field conditions.

The flight controller ensures stabilization of the drone's movement, maintaining a safe distance from the object and performing the planned mission. The LIDAR module transmits information on the current distance to the blade surface, allowing you to avoid collisions and accurately determine the position geometry during shooting. GPS/IMU provides spatial and temporal synchronization of all received data.

The processing results — defect type, coordinates, detection time, photo fixation — are transmitted via a communication channel to the ground station or stored locally on the Raspberry Pi's media in the event of communication loss. The ground station receives the information, generates analytical reports, and provides the operator with thermal or visual damage maps for maintenance planning.

The proposed architecture (Fig. 1) provides diagnostic autonomy, accuracy, and reliability even in challenging weather conditions and is easily integrated into wind turbine maintenance and condition-prediction systems.

This system provides for a blade identifier, so they can be distinguished both when analyzing blade condition and during repair, since they are not stationary and constantly rotate. This identifier can be applied during installation; usually, 1, 2, or 3 red stripes are used

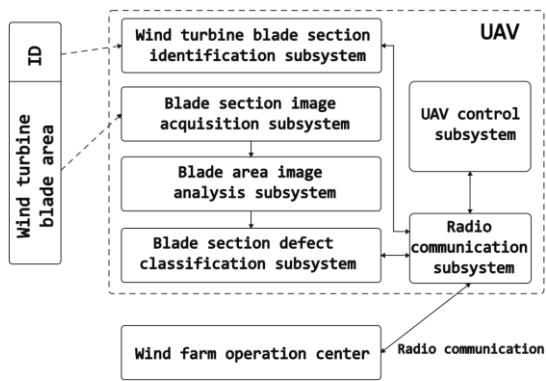


Fig. 1. Structure of the system for current analysis of the condition of wind turbine blades

to number the blades. Blade identification may be performed using pre-existing maintenance markings, rotor-position tracking, or vision-based association of the observed blade with the current inspection trajectory.

This information is fed to the wind farm blade section identification subsystem, which allows linking further damage analysis results to a specific blade and its damage location.

The blade section image acquisition subsystem prepares the image for submission to the CNN for analysis.

The blade section defect classification subsystem, based on the obtained analysis results, classifies the nature of the damage or its absence.

Using the radio communication subsystem, the system transmits the defect type, the corresponding image fragment, and the associated telemetry data to the ground station.

The UAV control subsystem is designed to control the execution of the flight mission, that is, the alternate flyby of each wind turbine blade.

2.2. Onboard subsystem of an unmanned aerial vehicle

Fig. 2 shows a block diagram of the onboard system of an unmanned aerial vehicle (UAV). This system, designed for the inspection of wind turbine blades, consists of several interconnected hardware modules: a video camera, a computing module, such as a Raspberry Pi5, a neural network accelerator (NPU), a flight controller, LIDAR sensors, a GPS module, a power system, and a communication system. All these elements are combined into a single integrated architecture that ensures stable flight, visual data collection, real-time processing, and transmission of results to the operator.

The video camera is the main sensor for collecting images of the blades. It is mounted on a stabilized platform or gimbal, allowing for clear images while the drone is moving.

The resulting video stream is fed directly to the processing system, where the frames are analyzed using artificial intelligence models to detect damage. Each frame is synchronized with telemetry data from the flight controller and GPS, allowing the precise location of the defect on the blade to be determined.

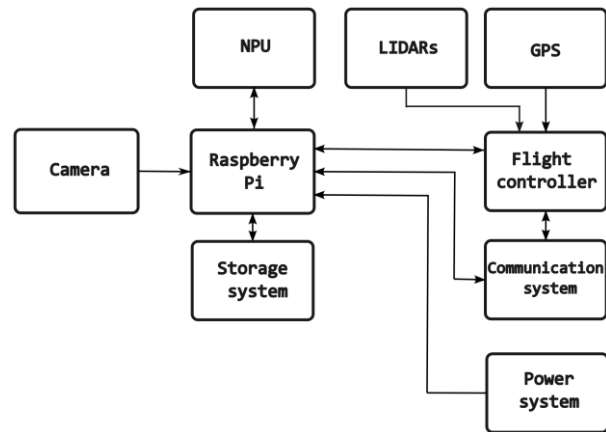


Fig. 2. Onboard subsystem of an unmanned aerial vehicle

The computing module (in this case, the Raspberry Pi 5) acts as the central computing node of the system. It deploys software modules for:

- collecting video stream from the camera;
- image pre-processing (noise filtering, stabilization, color alignment, scaling);
- running damage detection algorithms using NPU;
- data storage and labeling;
- communication with the flight controller, GPS, LIDAR and communication system.

Each frame is timestamped and linked to coordinates received from the flight controller via the MAVLink protocol. This allows us to determine not only the fact of damage, but also its exact geolocation on the blade surface.

The NPU (Neural Processing Unit) module connected to the Raspberry Pi provides hardware acceleration of the execution of neural models.

Its main task is to quickly detect and preliminarily characterize visually observable blade-surface conditions such as erosion, corrosion, crack, and pristine regions. Thanks to the use of optimized and quantized models (INT8), the system is able to perform analysis in real time, even in field conditions, without the need to connect to cloud services.

The flight controller, which runs on the ArduPilot firmware, is responsible for flight stabilization, mission routing, and signal processing from GPS, IMU, and other sensors.

Through the MAVLink protocol, it transmits

telemetry data to the Raspberry Pi 5 — current coordinates, altitude, speed, orientation (pitch angle, roll, heading), and also receives commands from a higher control level.

Thus, the flight controller not only ensures the safe movement of the drone but also provides the data necessary for the spatial reference of detected defects.

Drones use laser rangefinders (LIDARs) to maintain a safe distance from objects. In this case, we are only interested in the rangefinder that measures the distance between the drone and the blade surface. This information is necessary both to ensure a safe distance during the flyby and to determine the coordinates of defects in three-dimensional space more accurately.

LIDARs connect to the flight controller and help you maintain the required distance from the object during video recording. Its readings, together with GPS and IMU data, enable the system to reconstruct the drone's position relative to the inspection object.

A GPS (or GNSS, if possible, in RTK configuration) module provides accurate global coordinates. It is used by both the flight controller and the Raspberry Pi for data synchronization.

The PPS (Pulse Per Second) signal from the GPS can be fed to the Raspberry Pi to match video and telemetry timestamps accurately. This is especially important when linking detected defects to specific areas of the blade.

The power system provides a stable power supply to all UAV components. It consists of a battery, a power distribution board (PDB), voltage regulators (BEC), and current and voltage control modules.

Separate power branches are supplied to the power unit (motor system) and electronics (Raspberry Pi, camera, NPU, LIDAR, GPS). Filters and stabilizers are provided to protect against voltage surges and interference. This avoids malfunctions in the operation of computing modules when the load changes during flight.

The communication system includes two main channels: a telecommunications channel between the flight controller and the ground station (via a radio modem at 433 or 915 MHz). This channel is used for telemetry transmission, flight control, and mission command execution.

High-speed communication channel between Raspberry Pi and the operator or cloud server - via Wi-Fi, LTE, 5G modem or radio modem at a high frequency of 2.4 GHz or 5.8 GHz. This allows you to transfer video streams, damage detection results and service data.

The transmission is encrypted, which guarantees safe operation in the field. In case of loss of the main communication channel, the system goes into offline mode, and all results are stored locally in the built-in system (Storage System).

During the mission, the camera captures images of

the blades, the Raspberry Pi receives these frames, performs pre-processing, and passes them to the NPU for analysis.

In parallel, the flight controller sends telemetry data, and the LIDAR modules send the distance to the object. The Raspberry Pi combines all this information to create georeferenced records of detected damage.

The processing results can be transmitted in real time to a ground station or stored for further analysis in a cloud environment.

The proposed architecture enables autonomous, real-time operation of the blade damage identification system without an external computing server. Interaction between Raspberry Pi 5, NPU, flight controller, LIDARs, GPS and camera. This creates a flexible, reliable, and energy-efficient platform capable of accurately detecting and localizing defects, even under difficult operating conditions.

2.3. Data processing for blade damage detection and localization

As part of the onboard subsystem's operation, data processing is performed to detect and localize blade damage (Fig. 3).

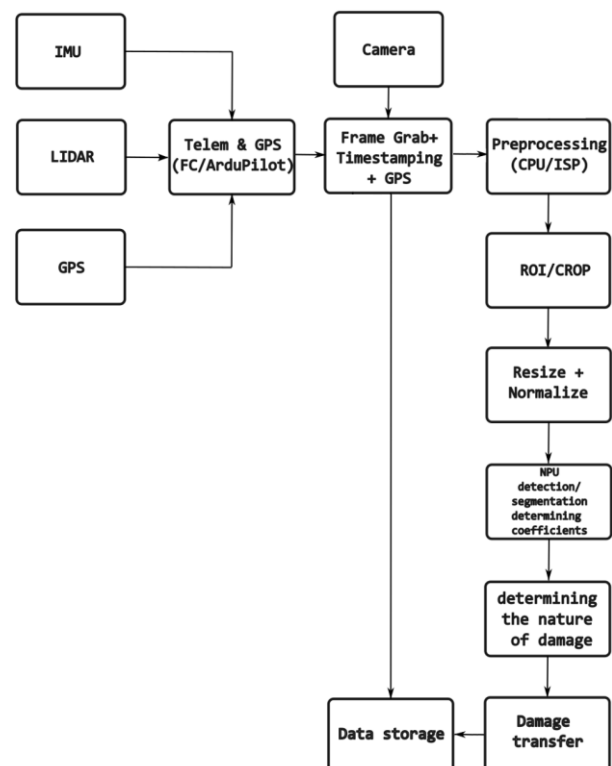


Fig. 3. Data processing scheme for blade damage detection and localization

A high-resolution camera captures video from which the necessary frames for analysis are selected and

telemetry data (time, position, etc.) is attached. Each frame from the camera receives an accurate timestamp (UTC) and a unique frame_id. The exact time must be synchronized with the PPS from the GPS/telem from the flight controller to ensure correct correspondence between the frame and the drone's orientation/position.

The Preprocessing module (CPU/ISP) performs frame stabilization, exposure correction/WDR, and noise reduction. Due to platform movement and blade oscillation, it is important to level the exposure and remove motion blur. With a sufficiently short shutter speed, you can get pretty clear frames that require minimal processing. A high-quality camera can ensure this and good lighting (shooting during the day, in cloudless weather).

The ROI/Crop module selects the area where the blade is located. This significantly reduces the amount of data to be processed further.

After ROI, the frame is resized to the expected model size and normalized using the Resize + Normalize module.

Defect detection and preliminary visual categorization are performed on the NPU using a lightweight YOLO-based model. For each detected region of interest, the detector produces class-related confidence coefficients corresponding to the predefined blade-surface states. These coefficients are then forwarded to the neuro-fuzzy decision module, which performs final classification and increases robustness in cases where detector confidences are close or partially ambiguous. After the final decision is obtained, the system stores the defect type together with the image fragment, timestamp, and telemetry attributes, and transmits the resulting georeferenced defect record to the ground station when the communication channel is available.

After a defect is detected, its type, photo, and telemetry data (coordinates, time, altitude) are sent to the ground station using the Damage Transfer module. They are also written to a local disk to prevent information loss in the event of communication failures.

The complete video stream together with synchronized telemetry is also recorded for subsequent offline analysis, verification, and dataset extension.

3. Results and Discussion

3.1. Case study

The wind turbine blade defect classification system is implemented on a Raspberry Pi 5 computing module, which provides sufficient computing power for real-time operation of damage detection and classification algorithms without the need for external accelerators. The software is based on the YOLOv5 (You Only Look

Once) neural model, adapted for execution on the ARM Linux platform using the OpenCV and PyTorch Lite libraries.

To trace the goal of the study formulated in the Introduction, the experimental validation was organized along three complementary dimensions: diagnostic performance, computational efficiency, and operational feasibility of onboard deployment. Diagnostic performance was assessed by classification-related indicators of the decision module and the integrated workflow; computational efficiency was assessed by frame rate and execution time per decision cycle; and operational feasibility was assessed by the ability to execute the full processing chain locally on Raspberry Pi 5 without mandatory cloud support.

The YOLO model detects regions of interest (ROIs) of the blade and generates four class coefficients for each region: Erosion, Corrosion, Crack, and Pristine. These coefficients are interpreted as the model's degree of confidence in the presence of the corresponding type of defect. The values of these coefficients are then fed to a neuro-fuzzy system (NFS), which integrates the results and provides a final decision on the blade state: Pristine, erosion (Erosion), corrosion (Corrosion), Crack.

Fig. 5 shows the interface for visualizing the results of the system on the Raspberry Pi. The left side of the screen displays the current image from the camera, and the right side displays a panel with the YOLO detection coefficients and the final solution of the neuro-fuzzy system. For each detected defect, the system also records the GPS coordinates, altitude, detection time, and confidence level.

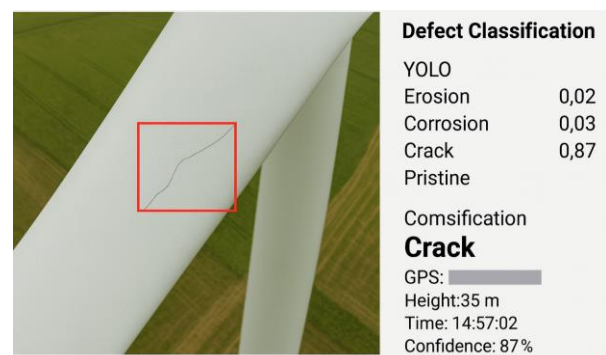


Fig. 5. Raspberry Pi 5 interface

In lab tests, the Raspberry Pi 5 achieved an average processing speed of 5–6 frames per second (FPS) at a resolution of 640×480 pixels. The average classification accuracy on the validation set was 88.1%, exceeding the established threshold of 85%. It should be noted that two accuracy values are reported in this study because they correspond to different stages of evaluation. The 88.1% value characterizes the validation accuracy of the integrated detection–classification workflow under embedded execution conditions. By contrast, the 94.0%

value reported below refers specifically to the neuro-fuzzy decision module evaluated on a separate test set of YOLO-derived class-coefficient vectors. Therefore, the first result reflects system-level performance, whereas the second quantifies the discrimination capability of the decision-level classifier under structured input conditions.

In the proposed work, a modified Wang–Mendel neural-fuzzy network adapted to the real-time multi-class recognition problem is used to classify wind turbine blade defects with increased accuracy. Unlike the classical approximation-oriented model, the proposed approach is supplemented with a multi-output structure and a cross-entropy-based learning criterion, which allows for efficient processing of feature vector streams generated by the YOLO neural network directly on low-power computing devices, in particular the Raspberry Pi.

The input vectors $x = \{x_1, \dots, x_N\} \in [0,1]^N$ are pre-normalized and fed to the fuzzification layer, where each feature is described by a set M of Gaussian membership functions of the form

$$\mu_{ij}(x_i) = \exp(-(x_i - c_{ij})^2/2\sigma^2).$$

The model uses fixed widths σ , which significantly reduces the number of parameters and speeds up calculations, which is critically important for working on the Raspberry Pi. The next aggregation layer forms a linguistic activation basis for each rule $\phi_1 = \prod_{i=1}^N \mu_{i1}$. Next, a linear combination of weight coefficients is formed for each defect class:

$$y_q = w_{q0} + \sum_{l=1}^M w_{ql} \phi_l,$$

where $q = 1, \dots, L$, and the final membership probabilities are calculated using softmax:

$$p_q = \exp(y_q) / \sum_s \exp(y_s).$$

The maximum value p_q determines the object class (erosion, corrosion, crack or normal state). The system is trained using the crossentropy criterion

$$E = -\sum_q d_q \ln p_q,$$

where d_q is the “one-hot” vector of the target class, and the weights are updated using the gradient rule

$$\Delta w_{ql} = -\eta(p_q - d_q)\phi_l,$$

supplemented by an optimized Kacmarz–Widrow–Hoff scheme to ensure fast convergence in non-stationary data streams. This modification allowed us to preserve the interpretability of fuzzy logic, reduce the time spent on

calculations, and avoid the problem of “exploding” gradients thanks to the possibility of regularization [33].

This combination of the YOLO detector and the NFS provides increased resistance to noise, varying lighting conditions, and changes in shooting angles. Testing of the developed neuro-fuzzy system for classifying types of damage to wind turbine blades was conducted on a test sample comprising 64 examples. Although this experiment confirms the feasibility and high discriminative ability of the neuro-fuzzy classifier, the reported result should be interpreted as a module-level evaluation obtained on a limited test set. Consequently, this value does not replace broader field-scale validation and should be considered together with the integrated system-level results reported above. Each example consisted of four input features (Erosion, Corrosion, Crack, Pristine) obtained from the output coefficients of the YOLO neural network, and the corresponding target damage class.

Fig. 6 shows the results of testing the neuro-fuzzy system in terms of execution time.

```

===== TEST RESULTS =====
Test MSE      : 0.0568
Test Accuracy : 94.00%
=====

Calculating execution time on test data...

Example 1:
Raw input: [0.02698379 0.88344519 0.88163735 0.00302017]
Prediction: 2.8206 → Class 3
Execution time: 0.000176 c

Example 2:
Raw input: [0.07785836 0.92550336 0.38517179 0.25703808]
Prediction: 2.0128 → Class 2
Execution time: 0.000170 c

Example 3:
Raw input: [0.43973976 0.25391499 0.70918954 0.00226513]
Prediction: 2.3669 → Class 2
Execution time: 0.000171 c

===== TIME STATISTICS =====
Number of examples : 64
Minimum time      : 0.000165 c
Average time      : 0.000167 c
Maximum time      : 0.000176 c
=====
pi@raspberrypi:~/Wang_Mendel $

```

Fig.6. Results of testing the execution time of the neuro-fuzzy system

The test results indicate high efficiency and consistency of the system. The Mean Squared Error (MSE) was 0.0686, indicating a slight deviation of the predicted values from the reference ones. The classification accuracy (Accuracy) reached 94.00%, demonstrating the ability of the model to correctly determine the type of damage in the vast majority of cases.

In addition to qualitative indicators, the time characteristics of the classification process were evaluated. The average execution time of one calculation cycle was 0.000167 s, with:

- minimum recorded processing time - 0.000165 s;
- maximum time - 0.000176 s.

The results obtained indicate high computational efficiency of the proposed system. This level of performance enables practical use in real-time mode, in particular on low-power computing devices such as the Raspberry Pi, without the need for additional hardware accelerators.

Analysis of individual examples showed the system's stability: across different sets of input coefficients, the predicted damage-class values remained consistent and aligned with the expected results. This confirms the correctness of the training and the consistency of the work of both the neural network and the fuzzy components of the system.

3.2. Discussion

Comparison of the proposed system with existing solutions confirms a significant advantages in terms of performance, autonomy and versatility. The prototype described in [23] implements a method for inspecting photovoltaic modules using a UAV equipped with RGB and thermal cameras. Defect detection in it is carried out by analyzing heat maps, where the main attention is paid to "hot spots" as indicators of element degradation. The classification algorithm is mostly heuristic in nature and is based on threshold values of temperature anomalies. Although the system is effective for detecting thermal defects, it remains sensitive to the influence of weather conditions, insolation angle and the level of panel contamination, which reduces accuracy under variable lighting conditions.

The architecture proposed in this work differs in a fundamentally different approach to defect analysis — it uses the YOLOv5 neural model, optimized for the limited resources of the Raspberry Pi 5, in combination with a neuro-fuzzy system for classifying damage types. Unlike the prototype system [23], the model is not limited to thermal data, but can work with RGB images obtained from the drone, which allows detecting visual defects – cracks, erosion, corrosion, and coating delamination. In addition, the proposed neuro-fuzzy system increases the stability of the results, especially in conditions of mixed or uncertain classes, where the detector probabilities are close in value.

In quantitative comparison, the experimental results confirm a higher accuracy and better performance of the proposed system in real-time mode. In particular, the average classification accuracy reached 94%, while in [23] the accuracy was about 87% at processing time delays of more than 1 s per frame. The developed model provides a speed of 5–6 FPS at a resolution of 640×480 pixels, which allows for continuous monitoring during the flight without frame loss. High performance is

achieved through the use of the NPU hardware accelerator and quantized INT8 models, which consume minimal energy.

An additional advantage is the ability to process data locally on board without the need to transmit images to the cloud, which increases safety, reduces latency and allows the system to be used in conditions of limited connectivity. Thanks to the integration of GPS, IMU and LIDAR modules, the system also provides accurate georeferencing of defects, which enables the formation of three-dimensional damage maps of panels or blades.

The proposed mobile intelligent system, despite its autonomy and efficiency, has a number of limitations that must be taken into account during real-world application. The classification quality remains sensitive to image collection conditions, in particular, to sudden changes in lighting, wind fluctuations, glare, and atmospheric interference that affect frame stability. The limited computing resources of the Raspberry Pi and NPU narrow the range of neural networks that can operate on board a UAV in real time, especially with multimodal sensors. The limited number of large, real-world datasets with various defects limits the model's generalizability when transitioning to new blade types or other wind farms. The system is also sensitive to inaccuracies in georeferencing and depends on the proper calibration of the camera and the drone's stabilization, which can lead to errors in defect localization. Due to its reliance on RGB analysis, the system is effective only for surface damage and cannot detect subsurface defects in composite materials. In addition, adapting the model to new geometric blade configurations requires additional training, and limitations on flight autonomy and energy consumption complicate lengthy inspections of large wind farms.

Despite the encouraging results, the identified limitations define several important directions for further research. First, the current version of the system is restricted to RGB-based recognition of visually observable surface defects and therefore does not address subsurface or internally developing composite damage. Second, broader generalization requires larger and more diverse datasets collected under real wind-farm conditions, including variation in blade geometry, environmental factors, and illumination scenarios. Third, the spatial accuracy of defect localization should be further improved through enhanced calibration, synchronization, and georeferencing procedures. Future work will therefore focus on extending the defect taxonomy, integrating multispectral or thermal sensing, improving blade-position and defect-location estimation, and enhancing the neuro-fuzzy decision module for more reliable processing of uncertain or previously unseen damage patterns.

4. Conclusions

The goal of this study was to develop and validate an integrated UAV-based hardware–software complex for real-time wind turbine blade defect detection and classification on resource-constrained embedded hardware. The reported results confirm that this goal was achieved at the prototype level.

The study demonstrated that the proposed architecture can perform onboard visual inspection, telemetry-assisted georeferencing, and final neuro-fuzzy decision support directly on Raspberry Pi 5 without mandatory cloud infrastructure. This confirms the operational feasibility of the system for autonomous or semi-autonomous wind turbine blade inspection tasks.

The goal of the study was confirmed in three principal aspects. First, diagnostic feasibility was demonstrated by successful recognition of four predefined blade-surface states: Erosion, Corrosion, Crack, and Pristine. In the integrated validation workflow, the system achieved 88.1% classification accuracy, whereas the neuro-fuzzy decision module evaluated separately on YOLO-derived coefficient vectors achieved 94.0% accuracy with an MSE of 0.0686. Second, real-time suitability was confirmed by stable onboard operation at 5–6 FPS for 640×480 video and by an average execution time of 0.000167 s per decision cycle. Third, deployment autonomy was confirmed by local processing, telemetry synchronization, and onboard result storage.

The obtained results indicate that combining a lightweight YOLO-based detection stage with a neuro-fuzzy decision module improves robustness under changing illumination, noise, and close class probabilities while preserving suitability for embedded execution. At the same time, the present prototype remains limited to visually observable surface defects and depends on the quality of image acquisition, calibration, and georeferencing.

Future research will focus on extending the defect taxonomy, increasing dataset diversity under real operating conditions, integrating multispectral or thermal sensing, improving spatial localization accuracy, and further enhancing the neuro-fuzzy decision module for more reliable handling of ambiguous and previously unseen defect patterns.

Therefore, the proposed system can be considered a functionally consistent prototype of an intelligent onboard diagnostic tool for wind turbine blade inspection, combining acceptable diagnostic accuracy, real-time performance, and embedded operational autonomy.

Contributions of authors: conceptualization and structure of defect detection system – **Oleg Zastavnyy**,

Lesia Dubchak, Volodymyr Kochan; formulation of tasks, analysis – **Lesia Dubchak, Volodymyr Kochan, Nadiia Vasylykiv**; development of mathematical model, software, verification – **Lesia Dubchak, Oleg Zastavnyy, Zenovii Bernas**; analysis of results, visualization – **Oleg Zastavnyy, Lesia Dubchak, Oleg Savenko**; final review and editing – **Oleg Savenko, Nadiia Vasylykiv**.

Conflict of Interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship, or otherwise, that could affect the research and its results presented in this paper.

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Data Availability

The data contains both real laser scanning results and synthetically generated examples created to simulate various types of defects. The used data will be made available upon reasonable request.

Use of Artificial Intelligence

The study used simulated data to test the proposed logic model. Data files and the model simulation file can be provided by the corresponding author upon reasonable request.

All the authors have read and agreed to the published version of this manuscript.

References

1. Kong, K., Dyer, K., Payne, C., Hamerton, I., & Weaver, P.M. Progress and trends in damage detection methods, maintenance, and data-driven monitoring of wind turbine blades – a review. *Renewable Energy Focus*, 2023, vol. 44, pp. 390–412. DOI: 10.1016/j.ref.2022.08.005.
2. Memari, M., Shakya, P., Shekaramiz, M., Seibi, A.C., & Masoum, M.A. Review on the advancements in wind turbine blade inspection: integrating drone and deep learning technologies for enhanced defect detection. *IEEE Access*, 2024, vol. 12, pp. 33236–33282. DOI: 10.1109/ACCESS.2024.3371493.

3. Zhang, S., He, Y., Gu, Y., He, Y., Wang, H., Yang, R., Chady, T., & Zhou, B. UAV-based defect detection and fault diagnosis for static and rotating wind turbine blades: a review. *Nondestructive Testing and Evaluation*, 2025, vol. 40(4), pp. 1691–1729. DOI: 10.1080/10589759.2024.2395363.
4. Zhang, Z., & Shu, Z. Unmanned aerial vehicle (UAV)-assisted damage detection of wind turbine blades: a review. *Energies*, 2024, vol. 17, iss. 15, article no. 3731. DOI: 10.3390/en17153731.
5. Heo, S.-J., & Na, W.S. Review of drone-based technologies for wind turbine blade inspection. *Electronics*, 2025, vol. 14, iss. 2, article no. 227. DOI: 10.3390/electronics14020227.
6. Vladov, S., Scislo, L., Sokurenko, V., Muzychuk, O., Vysotska, V., Sachenko, A., & Yurko, A. Helicopter turboshaft engines' gas generator rotor R.P.M. neuro-fuzzy on-board controller development. *Energies*, 2024, vol. 17, article no. 4033. DOI: 10.3390/en17164033.
7. Carnero, A., Martín, C., & Díaz, M. Portable motorized telescope system for wind turbine blades damage detection. *Engineering Reports*, 2025, vol. 7, iss. 1, article no. e12618. DOI: 10.1002/eng2.12618.
8. Zhu, Y., & Liu, X. A lightweight CNN for wind turbine blade defect detection based on spectrograms. *Machines*, 2023, vol. 11, iss. 1, article no. 99. DOI: 10.3390/machines11010099.
9. Zhang, C., Yang, T., & Yang, J. Image recognition of wind turbine blade defects using attention-based MobileNetv1-YOLOv4 and transfer learning. *Sensors*, 2022, vol. 22, iss. 16, article no. 6009. DOI: 10.3390/s22166009.
10. Mao, Y., Wang, S., Yu, D., & Zhao, J. Automatic image detection of multi-type surface defects on wind turbine blades based on cascade deep learning network. *Intelligent Data Analysis*, 2021, vol. 25, iss. 2, pp. 463–482. DOI: 10.3233/IDA-205143.
11. Xiaoxun, Z., & at al. Research on crack detection method of wind turbine blade based on a deep learning method. *Applied Energy*, 2022, vol. 328, article no. 120241. DOI: 10.1016/j.apenergy.2022.120241.
12. Kozlov, O. Information technology for designing rule bases of fuzzy systems using ant colony optimization. *International Journal of Computing*, 2021, vol. 20, iss. 4, pp. 471–486. DOI: 10.47839/ijc.20.4.2434.
13. Tarle, B., & Akkalaksmi, M. Improving classification performance of neuro-fuzzy classifier by imputing missing data. *International Journal of Computing*, 2019, vol. 18, iss. 4, pp. 495–501. DOI: 10.47839/ijc.18.4.1619.
14. Golovko, V., Savitsky, Y., Laopoulos, T., Sachenko, A., & Grandinetti, L. Technique of learning rate estimation for efficient training of MLP. *Proceedings of IJCNN*, 2000, vol. 1, pp. 323–328. DOI: 10.1109/IJCNN.2000.857856.
15. Bodyanskiy, Y., Deineko, A., Skorik, V., & Brodetskiy, F. Deep neural network with adaptive parametric rectified linear units and its fast learning. *International Journal of Computing*, 2022, vol. 21, iss. 1, pp. 11–18. DOI: 10.47839/ijc.21.1.2512.
16. Radiuk, P., Rusyn, B., Melnychenko, O., Perzynski, T., Sachenko, A., Svystun, S., & Savenko, O. Criticality assessment of wind turbine defects via multispectral UAV fusion and fuzzy logic. *Energies*, 2025, vol. 18, article no. 4523. DOI: 10.3390/en18174523.
17. Dubchak, L., Sachenko, A., Bodyanskiy, Y., Wolff, C., Vasylyuk, N., Brukhanskiy, R., & Kochan, V. Adaptive neuro-fuzzy system for detection of wind turbine blade defects. *Energies*, 2024, vol. 17, iss. 24, article no. 6456. DOI: 10.3390/en17246456.
18. Shihavuddin, A.S.M., Chen, X., Fedorov, V., Nymark Christensen, A., Riis, N.A.B., Branner, K., Dahl, A.B., & Paulsen, R.R. Wind turbine surface damage detection by deep learning-aided drone inspection analysis. *Energies*, 2019, vol. 12, iss. 4, article no. 676. DOI: 10.3390/en12040676.
19. Sheiati, S., Jia, X., McGugan, M., & at al. Artificial intelligence-based blade identification in operational wind turbines through similarity analysis aided drone inspection. *Engineering Applications of Artificial Intelligence*, 2024, vol. 137, article no. 109234. DOI: 10.1016/j.engappai.2024.109234.
20. Shafiee, M., Zhou, Z., Mei, L., Dinmohammadi, F., Karama, J., & Flynn, D. Unmanned aerial drones for inspection of offshore wind turbines: a mission-critical failure analysis. *Robotics*, 2021, vol. 10, iss. 1, article no. 26. DOI: 10.3390/robotics10010026.
21. Kulsinkas, A., Durdevic, P., & Ortiz-Arroyo, D. Internal wind turbine blade inspections using UAVs: analysis and design issues. *Energies*, 2021, vol. 14, iss. 2, article no. 294. DOI: 10.3390/en14020294.
22. Hu, W., Fang, J., Zhang, Y., Liu, Z., Verma, A.S., Liu, H., Cong, F., & Tan, J. Digital twin of wind turbine surface damage detection based on deep learning-aided drone inspection. *Renewable Energy*, 2025, vol. 241, article no. 122332. DOI: 10.1016/j.renene.2024.122332.
23. Liao, K.-C., & Lu, J.-H. Using UAV to detect solar module fault conditions of a solar power farm with IR and visual image analysis. *Applied Sciences*, 2021, vol. 11, article no. 1835. DOI: 10.3390/app11041835.
24. Masita, K., Hasan, A.N., Shongwe, T., & Hilal, H.A. Deep learning in defect detection of wind turbine blades: a review. *IEEE Access*, 2025, vol. 13, pp. 98399–98425. DOI: 10.1109/ACCESS.2025.3569799.
25. Dimitrova, M., Aminzadeh, A., Meiabadi, M. S., Sattarpanah Karganroudi, S., Taheri, H., & Ibrahim,

H. A survey on non-destructive smart inspection of wind turbine blades based on Industry 4.0 strategy. *Applied Mechanics*, 2022, vol. 3, iss. 4, pp. 1299–1326. DOI: 10.3390/applmech3040075.

26. Deng, L., Guo, Y., & Chai, B. Defect detection on a wind turbine blade based on digital image processing. *Processes*, 2021, vol. 9, iss. 8, article no. 1452. DOI: 10.3390/pr9081452.

27. Laib, L., Obeidi, T., Bensaci, A., & Naas, T. T. Drone-based inspection of wind turbine blades: a comparative study of deep learning models. *Studies in Engineering and Exact Sciences*, 2024, vol. 5, iss. 2, article no. e8248. DOI: 10.54021/seesv5n2-252.

28. Sherimon, P. C., Sherimon, V., Joy, J., Kuruvilla, A. M., & Arundas, G. Efficient Deep Learning Methods for Detecting Road Accidents by Analyzing Traffic Accident Images. *International Journal of Computing*, 2024, vol. 23, iss. 3, pp. 440-449. DOI: 10.47839/ijc.23.3.3664.

29. Lysenko, V., Opryshko, O., Komarchuk, D., Pasichnyk, N., Zaets, N., & Dudnyk, A. Information support of the remote nitrogen monitoring system in agricultural crops. *International Journal of Computing*, 2018, vol. 17, iss. 1, pp. 47-54. DOI: 10.47839/ijc.17.1.948.

30. Iannace, G., Ciaburro, G., & Trematerra, A. Fault diagnosis for UAV blades using artificial neural network. *Robotics*, 2019, vol. 8, iss. 3, article no. 59. DOI: 10.3390/robotics8030059.

31. Li, B.L., Feng, C.Q., Wei, S.H., & Liu, Y.F. Concrete wind turbine tower crack assessment based on drone imaging using computer vision and artificial intelligence. *Advances in Structural Engineering*, 2025, article no. 13694332251344664. DOI: 10.1177/13694332251344664.

32. Rodriguez, A. A., Davis, M., Zander, J., Nazario Dejesus, E., Shekaramiz, M., Memari, M., & Masoum, M.A. Deep learning for indoor pedestal fan blade inspection: utilizing low-cost autonomous drones in an educational setting. *Drones*, 2024, vol. 8, iss. 7, article no. 298. DOI: 10.3390/drones8070298.

33. Reddy, A., Indragandhi, V., Ravi, L., & Subramaniaswamy, V. Detection of cracks and damage in wind turbine blades using artificial intelligence-based image analytics. *Measurement*, 2019, vol. 147, article no. 106823. DOI: 10.1016/j.measurement.2019.07.051.

34. Dubchak, L., Bodyanskiy, Y., Sachenko, A., Wolff, C., Vivchar, N., & Vasylykiv, N. Modified neuro-fuzzy system for online classification of wind turbine blade defects. *IEEE Access*, 2025, vol. 13, pp. 166841–166852. DOI: 10.1109/ACCESS.2025.3612267.

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ІНТЕГРОВАНІЙ АПАРАТНО-ПРОГРАМНИЙ КОМПЛЕКС ДЛЯ КЛАСИФІКАЦІЇ ДЕФЕКТІВ ЛОПАТЕЙ ВІТРОВИХ ТУРБІН

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Предметом дослідження у статті є інтегрований апаратно-програмний комплекс для виявлення та класифікації дефектів лопатей вітрових турбін у режимі реального часу з використанням безпілотного літального апарата (БПЛА), оснащеного бортовими модулями edge-AI. **Метою** дослідження є розробка та експериментальна валідація автономної вбудованої платформи, здатної здійснювати збір, обробку та інтерпретацію зображень поверхні лопатей у польових умовах із забезпеченням достатньої діагностичної точності та роботи в режимі реального часу на обмежених обчислювальних ресурсах. **Завданнями** дослідження є: проектування архітектури системи інспекції на базі БПЛА; реалізація бортового конвеєра обробки даних, що включає отримання зображень, попередню обробку, виявлення дефектів, їх класифікацію та геоприв'язку результатів; розробка полегшеного етапу візуального виявлення дефектів на основі YOLO у поєднанні з нейро-нечітким модулем прийняття рішень; а також оцінювання діагностичної та обчислювальної ефективності запропонованої системи на платформі Raspberry Pi 5. Застосовані **методи** включають полегшений глибинний аналіз зображень, нейро-нечітке виведення на основі гаусових функцій належності та адаптації типу Ванга–Менделя, геоприв'язку дефектів із використанням телеметричних даних, а також експериментальну оцінку в умовах обмежених вбудованих обчислювальних ресурсів. Отримані **результати** показали, що розроблений прототип забезпечує стабільну бортову роботу зі швидкістю 5–6 кадрів за секунду (FPS) для відео з роздільною здатністю 640×480, підтримує локальну обробку без використання хмарної інфраструктури та забезпечує надійне розпізнавання стану поверхні лопаті за чотирма попередньо визначеними класами: ерозія, корозія, тріщина та бездефектний стан. У межах інтегрованого процесу валідації система досягла точності класифікації 88,1%, тоді як нейро-нечіткий модуль прийняття рішень, оцінений окремо на векторах коефіцієнтів класів, отриманих із YOLO, досяг точності 94,0% при середньоквадратичній

помилці (MSE) 0,0686. **Висновки.** Наукова новизна полягає у розробці повністю автономної діагностичної архітектури на основі БПЛА, яка поєднує бортове візуальне виявлення дефектів, злиття телеметричних даних і нейро-нечітку підтримку прийняття рішень на обмежених вбудованих обчислювальних ресурсах, а також у адаптації нейро-нечіткого класифікатора для багатокласового оцінювання стану лопатей у режимі реального часу.

Ключові слова: лопаті вітрових турбін; інспекція БПЛА; виявлення дефектів; глибинне навчання; нейро-нечітка система; edge-AI; YOLO; Raspberry Pi.

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