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Cascade Neuro-Fuzzy System Architecture for Classification of Renewable Energy Facilities Defects

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ABSTRACT The article proposes a hybrid cascaded neuro-fuzzy system for classifying defects in renewable energy facilities based on multisensor data. The system architecture implements a sequence of computational levels (from sensor acquisition and preprocessing to result integration) and combines a compact feature representation with adaptive decision-making logic. The formation of a compact feature space is carried out using a modified convolutional neural network, after which the initial classification is performed using the hypersector FLVQ method. In cases of increased uncertainty, the expert modules Fuzzy BSB and the modified Wang–Mendel method are activated, which ensures robustness and explainability of the results. Experimental studies have shown that the proposed system provides consistently high Accuracy values (over 94%), balanced Precision and Recall indicators for all defect classes. Analysis of the discrepancy matrix showed that the main errors occur between the "erosion" and "corrosion" classes, which is explained by the similarity of their textural characteristics. The results obtained confirm the effectiveness of the cascade architecture and its feasibility for practical application in automated monitoring systems for renewable energy facilities.

KEYWORDS intelligent monitoring; renewable energy; defect classification; neuro-fuzzy systems; cascade architecture; FLVQ; Fuzzy BSB; Wang–Mendel method

I. INTRODUCTION AND RELATED WORK

The rapid growth of renewable energy capacity increases the requirements for reliability and predictive maintenance of key infrastructure elements, primarily wind turbine blades and photovoltaic (PV) modules. For wind turbines, blades are the most loaded and vulnerable components, and defects such as cracks, edge erosion or local surface damage can lead to aerodynamic degradation, increased vibrations and unplanned downtime. In this work, the focus is placed on the most representative and practically significant defect types, namely cracks, erosion, corrosion, and normal surface condition. These defects are selected because they reflect different physical degradation mechanisms and have a direct impact on the operational reliability of renewable energy systems. In particular, cracks correspond to structural integrity violations and may lead to catastrophic failure, erosion affects aerodynamic performance and reduces energy efficiency, while corrosion represents long-term material degradation processes. The inclusion of the normal state is necessary to ensure reliable discrimination between defective and non-defective conditions.

Current reviews emphasize that the transition from manual inspections to UAV inspections provides better safety and scalability, but places new requirements on data quality, flight stability, georeferencing accuracy and automation of analytics [1-3].

In the PV power plant segment, the problem is similar: hot-spot defects, cell degradation, faulty bypass diodes, contamination or partial shading directly affect generation and can be detected using UAV thermal imaging [4, 5]. Practice shows that the most promising approaches are those where infrared data are used for initial detection of anomalies/overheating, and deep learning algorithms perform segmentation or detection of defective areas on a large-scale plant scale. In particular, [6] demonstrated the effectiveness of DL-segmentation of defects on UAV thermal images (U-Net/DeepLabV3+/FPN) and systems based on Mask R-CNN [7] for searching for damaged cells.

However, the dominance of "heavy" deep learning models creates typical limitations for real-world operation [8]: (i) the need for large, well-labeled datasets; (ii) high computational cost when working "at the edge" or in resource-constrained environments; (iii) difficulty in explaining solutions (low interpretability), which is critical for technical diagnostics and regulatory decision-making. In wind energy, this is manifested in the desire to combine the accuracy of deep learning (DL) detectors with mechanisms for increasing robustness/reliability (e.g., ensemble and fuzzy voting) and with the practical requirements of UAV inspection.

Modern DL approaches demonstrate high accuracy rates in defect detection tasks. For example, in [9] a system based on Mask R-CNN with fuzzy voting was proposed, which on a set of UAV images (3000 frames) achieved mean Average Precision mAP = 80.10%, surpassing individual CNN models and demonstrating high robustness in detecting cracks, holes and erosion. Similarly, modern DL architectures for defect classification (YOLO- or ViT-based) provide accuracy up to 97.8% and an average inference time of about 20 ms/image but require significant computational resources and a large amount of training data.

Neuro-fuzzy systems constitute a separate class of effective analogues. Recent studies also confirm the effectiveness of hybrid neural and fuzzy models for classification tasks in complex data environments, including approaches that combine neural networks with fuzzy logic for improved interpretability and robustness [10]. In particular, the adaptive ANFIS system for detecting blade defects proposed in [11] provides about 91% accuracy with lower computational complexity and the ability to work with fuzzy data. Further development of fuzzy systems is demonstrated in the work [9], where multispectral UAV data is combined with a fuzzy system for assessing the criticality of defects. A review of modern methods shows that fuzzy approaches allow detecting defects several days earlier than traditional methods of analyzing SCADA data.

Classical ML approaches (e.g. HOG+SVM with log-Gabor features) demonstrate accuracy above 92% but are characterized by lower noise immunity and poor generalization ability in complex scenarios [12]. This limits their application in automated UAV monitoring tasks.

A separate direction that is becoming relevant specifically for engineering monitoring systems is hybridization [13-16]: cascade architectures, where the first level performs fast and "cheap" extraction of informative features/candidates, and subsequent levels implement more complex classification, verification, or explained decision-making logic. For wind turbines, such approaches are actively developing both in the form of methods for detecting defects on UAV images and in the form of fully automated pipelines for blade inspection; similarly, in the PV field, as a combination of thermography, computer vision, and ML/DL for diagnosing defects from infrared data [17].

It should be noted that although end-to-end deep learning architectures dominate in modern image analysis tasks, cascade-based approaches remain relevant in scenarios with limited computational resources and real-time constraints. In particular, for UAV-based inspection systems and edge computing environments, cascade architectures allow adaptive allocation of computational effort, where complex processing is activated only in uncertain cases. This makes such architectures more suitable for practical deployment compared to monolithic models that require constant high computational load.

Although cascade architectures are less frequently used in end-to-end deep learning pipelines, they remain highly relevant for resource-constrained and embedded intelligent systems. In such scenarios, cascade organization enables efficient allocation of computational resources by activating complex processing modules only, when necessary, which is critical for real-time edge deployment.

Thus, the analysis of modern scientific sources shows that, despite significant progress in the application of machine learning methods and deep neural networks for diagnosing defects in renewable energy facilities, there are a number of fundamental limitations that hinder their widespread implementation in real monitoring systems. In particular, most DL approaches demonstrate high accuracy only in the presence of large and well-labeled samples, which is difficult for practical scenarios of inspection of wind turbine blades and solar panels. In addition, the computational complexity of modern models complicates their use on edge platforms and UAV onboard systems, and the low interpretability of the results limits the possibilities of integration into routine technical diagnostic procedures [18-20].

On the other hand, classical fuzzy and neuro-fuzzy approaches provide better explainability and robustness to uncertainties but are inferior to deep models in terms of accuracy in complex scenarios with overlapping classes [21]. Therefore, there is an objective need to create a hybrid intelligent system that would combine the advantages of deep learning (high discriminative ability), fuzzy models (interpretability and robustness) and cascade architectures (resource efficiency and adaptability to operating conditions). It is this approach that allows minimizing the expected risk of errors, ensuring a balance between accuracy, speed and computational complexity, as well as forming explainable diagnostic solutions for practical use in renewable energy monitoring systems.

The work aims to develop and experimentally substantiate a cascaded neuro-fuzzy system for detecting and classifying defects in renewable energy facilities, capable of functioning effectively in conditions of limited data, resource constraints, and uncertainties of the real operating environment.

To achieve the set goal, the following tasks were formulated in the work:

- To analyze modern approaches to automated diagnostics of defects in renewable energy facilities and determine their limitations in conditions of limited resources and uncertainties.
- Develop a mathematical model of the degradation of renewable energy facilities and a method for forming a compact feature space for effective data representation.
- To synthesize a hybrid cascaded neuro-fuzzy architecture based on a combination of Fuzzy Learning Vector Quantization (FLVQ), Fuzzy “Briane State in the Box” (BSB), and the Wang–Mendel method.
- Develop an algorithm for the functioning of a system with adaptive switching logic between classifiers.
- Conduct experimental testing of the system and comparative analysis with modern analogues based on key performance indicators.

In contrast to purely deep learning-based solutions, the proposed cascade neuro-fuzzy architecture is specifically designed for operation under limited data and computational constraints. Its effectiveness is determined by three key factors: (i) the use of a compact feature representation that significantly reduces dimensionality and computational cost; (ii) adaptive switching between classifiers, which enables robust decision-making under uncertainty; and (iii) the integration of explainable neuro-fuzzy models, which allows interpretation of classification results in engineering diagnostics. This makes the proposed approach particularly suitable for early defect detection and reliable operation in real-world UAV-based monitoring systems.

II. MATHEMATICAL MODEL OF DEGRADATION OF A RENEWABLE ENERGY FACILITY

Renewable energy objects, in particular wind turbine blades and photovoltaic modules, should be considered as complex dynamic technical systems, the technical condition of which is formed under the influence of degradation processes, external operational factors and the accumulation of defects over time. To formalize the degradation processes, a generalized mathematical description is used, which establishes a connection between the physical state of the object, measured parameters and the results of intelligent diagnostics. State of the renewable energy systems (RES) object at a point in time t is described by a state vector $x(t) \in \mathbb{R}^n$, whose components include mechanical, electrical, geometric, and thermal characteristics of the system that determine its ability to perform the energy conversion function. The state space is denoted by X, the set of defects by D, the set of external influences by U, and the set of measured parameters by Y [22].

The dynamics of the system state change under the influence of degradation, defects and external conditions can be presented in the form of a linear generalized state model: $\dot{x}(t) = Ax(t) + Gd(t) + Bu(t)$, where $A \in \mathbb{R}^{n \times n}$ is a matrix of natural degradation, reflecting the slow processes of material aging and the accumulation of microdamage; G – matrix of the influence of defects on the state parameters; $d(t)$ – defect vector; B – matrix of external influences; $u(t)$ – vector of operating conditions (wind speed, temperature, solar radiation, mechanical loads, etc.). It should be noted that the presented model is a simplified linear approximation of the degradation process. In real operating conditions, the evolution of the system state is inherently nonlinear due to complex interactions between environmental factors, material fatigue, and defect propagation mechanisms. However, the linear formulation is adopted as a tractable approximation that enables analytical representation, simplifies parameter estimation, and ensures compatibility with subsequent intelligent classification procedures. In discrete form, the model takes the form $x_{k+1} = Ax_k + Gd_k + Bu_k$, which allows taking into account the gradual accumulation of degradation when analyzing time series.

The measured parameters of the system are related to the state by the relation $y(t) = Cx(t) + \varepsilon(t)$, where C is the observation matrix, and $\varepsilon(t)$ – measurement noise, which takes into account sensor errors, lighting instability, atmospheric effects and other factors typical of UAV inspection. This setting corresponds to real operating conditions, when condition assessment is performed based on indirect measurements.

The performance of an object is determined by a function of state, defects and external influences: $P(t) = f(x(t), d(t), u(t))$. For wind turbines it can be given as $P_w = \frac{1}{2}\rho A v^3 C_p \eta$, where ρ – air density, A – rotor area, v – wind speed, C_p – energy utilization factor, η – overall efficiency [23]. The presence of defects leads to a decrease in efficiency coefficients, which is formalized by $C_p' = C_p(1 - \delta_d)$. For photovoltaic systems, the efficiency is defined as $P_{pv} = GA\eta_{pv}$, where G is the radiation intensity, and the degradation is described as $\eta_{pv}' = \eta_{pv}(1 - \delta_d)$. The relative degradation of performance is determined by the indicator $\delta(t) = \frac{P_{nom}(t) - P(t)}{P_{nom}(t)}$, which is an integral characteristic of the technical condition [24].

The reliability of the system is determined by the probability of being in a working condition $R(t) = P(x(t) \in \Omega)$, where Ω – the range of permissible states. The margin of operability can be represented as the distance to the critical failure state $r(t) = \| x(t) - x_{crit} \|$, which allows us to estimate the risk of failure in time. Within this model, the diagnostic task is formulated as the evaluation of defects by measured parameters: $\hat{d}(t) = \Phi(y(t))$, where $\Phi(\cdot)$ – intelligent classification operator.

To ensure reliable classification of defects, the model training problem is formalized as the minimization of a risk-oriented functional. To ensure reliable classification of defects, the training problem is formulated as the minimization of a cost-sensitive empirical risk functional.

Let x_i denote the feature vector, y_i the true class label, and $\hat{y}_i$ the predicted class. Then the empirical risk is defined as $R = \frac{1}{N}\sum_{i=1}^{N} L(y_i, \hat{y}_i)$, where N is the number of samples in the dataset, and $L(y_i, \hat{y}_i)$ is a loss function determined by the error cost matrix. In this work, the loss function is defined in a cost-sensitive form $L(y_i, \hat{y}_i) = C(y_i, \hat{y}_i)$, where C is the cost matrix that assigns higher penalties to misclassification of critical defects (e.g., cracks) compared to less critical ones (e.g., erosion). Such a formulation allows taking into account not only classification accuracy but also the reliability of decisions and the practical significance of different types of errors. This approach is consistent with the practical requirements of monitoring systems, where incorrect classification of structurally critical defects may lead to significantly higher risks than errors in less critical cases. From a theoretical perspective, this formulation corresponds to the minimization of expected risk under non-uniform misclassification costs.

Therefore, the proposed mathematical model forms a holistic theoretical basis for analyzing the degradation of renewable energy facilities, provides a formal connection between the technical condition, defects, and performance, and creates the prerequisites for building a hybrid cascade diagnostic system, as considered in the following sections of the article.

III. VECTOR FORMATION

One of the key problems of intelligent diagnostics of defects in renewable energy facilities is the excessive dimensionality of the input data. Images of wind turbine blades or solar panels obtained from UAVs contain a large amount of pixel information, but only a small part of it directly characterizes the defective state of the object. The use of such data in its original form leads to an increase in computational complexity, increased memory requirements and an increase in decision-making time, which is critical for real-time systems. That is why one of the basic stages of the intelligent system proposed in this article is the formation of a compact feature space in which multidimensional visual information is transformed into a low-dimensional but informative representation suitable for further classification by neuro-fuzzy methods.

In general terms, this stage can be represented as a representation $z = \Psi(I)$, where I – input image or frame fragment, and $z \in \mathbb{R}^m$ – compact feature vector. In the proposed architecture, $m = 4$, i.e., each defective fragment after processing is represented by a four-dimensional feature vector. This choice provides significant information compression compared to the pixel space and allows maintaining sufficient discrimination ability to separate the main classes of states, for example, "erosion", "corrosion", "crack", "normal state".

The formation of a compact feature space in the proposed system is performed using a modified convolutional neural network SqueezeNet. The choice of this architecture is due to its high parametric efficiency. Unlike deep CNNs with a large number of parameters, SqueezeNet provides similar quality of feature extraction with significantly lower memory and computational requirements, which makes it suitable for embedded edge systems. Architecturally, SqueezeNet is based on the so-called fire modules, which consist of a compression layer 1×1 and expansion layers 1×1 and 3×3 [25]. This construction allows to significantly reduce the number of network parameters without significant loss of discriminatory ability. For the task of inspection of renewable energy facilities, this is especially important, since the processing must be performed either directly on board the UAV or on a limited edge platform in the ground segment.

Before the image is fed to the feature extraction module, preprocessing is performed. Its goal is to eliminate variability that is not related to the defect itself. Such factors include changes in lighting, shooting scale, viewing angle, platform vibrations, local camera sensor noise, and compression artifacts. Formally, preprocessing can be represented as a sequence of operators

$$I^* = \mathcal{N}(\mathcal{R}(\mathcal{S}(I))), \quad (1)$$

where $\mathcal{S}$ – stabilization and alignment of the area of interest, $\mathcal{R}$ – scaling to a fixed size, $\mathcal{N}$ – normalization of intensities. As a result, a standardized image I^* is fed to the network input, for which the influence of external factors is reduced and the role of structural features of the surface is enhanced. This allows the network to focus not on random fluctuations, but on those patterns that really correspond to defects.

Inside the convolutional network, a multi-level transformation of the image into the space of corresponding features occurs. At the initial layers, the network detects low-level characteristics such as contours, brightness transitions, textural inhomogeneities, local gradients and microrelief. At the middle layers, sensitivity is formed to more complex structures - linear cracks, erosion spots, corrosion damage zones, areas of anomalous heating or violation of surface uniformity. At deeper levels, these local patterns are generalized into a more abstract representation of the defect state. If we denote the activations of the last convolutional layer as a tensor $F \in \mathbb{R}^{h \times w \times c}$, then the global generalization can be presented in the form of a global averaging operation:

$$g_k = \frac{1}{hw} \sum_{i=1}^{h} \sum_{j=1}^{w} F_{ijk}, k = 1, \ldots, c, \quad (2)$$

where h and w denote the spatial dimensions (height and width) of the feature map, and c is the number of channels in the convolutional representation.

Thus, a vector of high-level features is formed $g = [g_1, g_2, \ldots, g_c]$.

However, this vector is still too dimensional for further use in a compact cascade system. Therefore, after the global averaging block, a projection into a low-dimensional space is applied:

$$z = Wg + b, \quad (3)$$

where $W \in \mathbb{R}^{4 \times c}$ is the linear transformation matrix, $b \in \mathbb{R}^4$ is the shift vector. As a result, a four-dimensional vector is formed

$$z = [z_1, z_2, z_3, z_4]. \quad (4)$$

A feature of the proposed approach is that these four components are not considered only as abstract numbers. They are interpreted as a compact semantic representation of the object state. In the simplest case, each component corresponds to a tendency to a certain class of defect or to a certain type of structural anomaly. For example, one component may be more sensitive to linear surface irregularities, another to textural degradation, a third to signs of thermal anomaly, and a fourth to the preserved normal state. Such an interpretation does not mean a strict correspondence "one feature – one defect", but it makes the feature space more understandable for subsequent fuzzy classifiers. This is why the four-dimensional space becomes not just compressed, but also structured.

To ensure the correct operation of subsequent classification modules, the generated feature vector must be normalized. If the components z_i will have different scales, this will lead to distortion of the metric and displacement of the boundaries between classes. Therefore, normalization is used, for example, in the form

$$\tilde{z}_i = \frac{z_i - \mu_i}{\sigma_i}, \quad (5)$$

where μ_i and σ_i – the mean value and standard deviation of the corresponding feature in the training sample. In some cases, normalization to a unit norm can also be used

$$\hat{z} = \frac{\tilde{z}}{\|\tilde{z}\|}. \quad (6)$$

This is especially useful for methods that are more sensitive to the direction of a vector than its absolute length. After such processing, the compact vector becomes more scale-invariant and suitable for stable class separation.

An important property of a compact feature space is its ability to combine information from different sources. Although the basic version of the system uses visual RGB images, the structure of the space itself is not limited to this type of data. If necessary, thermal, laser, geometric or energy parameters can be integrated into the feature formation stage. Then the extraction function takes the form

$$z = \Psi(I_{rgb}, I_{th}, L, \Delta P), \quad (7)$$

where I_{rgb} – visible image, I_{th} – thermal imaging, L – laser or geometric channel, ΔP – power change. In such a setting, the compact feature space also plays the role of a unified interface between heterogeneous sensor sources and the decision-making module. This is especially valuable for the task of monitoring renewable energy sources, where defects often appear not in one, but in several measuring channels simultaneously.

From the point of view of recognition theory, the formation of a compact feature space can be interpreted as the problem of constructing such a mapping Ψ, for which the intraclass variation decreases and the interclass variation increases. Formally, this means the desirability of fulfilling the conditions

$$\| z_i - z_j \| \to \min, \text{if } y_i = y_j, \quad (8)$$

and

$$\| z_i - z_j \| \to \max \text{ , if } y_i \neq y_j. \quad (9)$$

It is this property that ensures the further effectiveness of neuro-fuzzy classifiers. If the feature space is formed qualitatively, then the defect classes acquire a more expressive geometric structure: clusters, hypersectors, and fuzzy membership regions are formed, which greatly facilitates the work of FLVQ, FBSB, and Wang–Mendel. Conversely, in the case of poor-quality mapping, even a complex classifier will be forced to work in conditions of strong class overlap.

Separately, the resource aspect should be emphasized. If the initial image has a size $H \times W \times 3$, then its direct use in the classification module means working with a dimensional space $3HW$. For a typical frame, this is hundreds of thousands of parameters. Switching to a vector of four components means reducing the dimensionality by several orders of magnitude. Accordingly, the memory required to store one representation is reduced to

$$M_z = 4 \cdot s, \quad (10)$$

where s is the number of bytes per component. For the float32 type, this is only 16 bytes per sample, which is extremely important for processing streaming data on embedded devices. In addition, dimensionality reduction directly affects the time of subsequent classification, since all subsequent methods no longer work with a pixel matrix, but with a compact numerical description. This is what makes the cascade architecture practically implemented in real time.

Another significant advantage of a compact feature space is its suitability for explanatory analysis. Unlike the classical "deep" latent space of high dimension, the four-dimensional representation allows for partially tracing the logic of feature changes and their mutual influence. For neuro-fuzzy models, this means the possibility of constructing membership functions for each coordinate, forming fuzzy rules and analyzing the boundary regions between classes. For example, a rule of the type "IF z_1 is high AND z_3 is medium THEN defect = crack" becomes meaningful only when the features themselves have a stable and relatively interpretable nature. Thus, the stage of forming a compact space is critically important not only for speed, but also for the further interpretability of the system as a whole.

IV. NEURO-FUZZY CLASSIFIERS

In the proposed intelligent system for diagnosing defects in renewable energy facilities, a key role is played by the decision-making block, which is implemented on the basis of neuro-fuzzy classifiers. The use of this class of methods is justified by their ability to combine the learning ability of neural networks with the explainability of fuzzy models, which is critically important for technical diagnostics tasks. Unlike purely statistical or deep models, neuro-fuzzy systems allow the formation of structured decision-making rules, provide resistance to noise and incomplete data, and maintain high discrimination ability in cases of class overlap.

Within the proposed cascade architecture, three complementary classifiers are used: a hypersector method based on FLVQ, a fuzzy-associative model Fuzzy BSB, and a modified Wang–Mendel method. All of them work with a compact four-dimensional feature vector formed at the previous stage, which allows for a single unified decision space.

The hypersector method based on FLVQ is the main classifier of the system and performs the initial separation of defect classes in the feature space [26]. Its mathematical basis is based on the representation of each class by a set of prototypes w_k that define the geometric structure of the corresponding region. For the input feature vector z the Euclidean distance to the prototypes is calculated:

$$d_k = \| z - w_k \|. \quad (11)$$

Unlike classical LVQ, the hypersector approach also takes into account the direction of the vector in the feature space, which is formalized through the angular metric:

$$\alpha_k = \arccos \frac{z \cdot w_k}{\|z\| \|w_k\|}. \quad (12)$$

Combining the radial and angular components allows us to describe classes as hypersectors rather than spherical regions, which better corresponds to the nature of the defect distribution. The degree of membership in a class is determined by the function

$$\mu_k(z) = \exp(-\beta d_k), \quad (13)$$

where β is the scaling factor. Prototype training is performed according to the competitive learning rule:

$$w_k(t+1) = w_k(t) + \eta(t)(z - w_k(t)), \quad (14)$$

where $\eta(t)$ is the learning coefficient. Thanks to this geometric interpretation, the method provides high classification accuracy, especially in conditions of overlapping classes and gradual degradation of the surface of RES objects.

The second important component is Fuzzy BSB (Bidirectional Associative Memory with Fuzzy Logic), which acts as a robust classifier in cases of increased noise or instability of features [27]. Its work is based on the representation of classes as hyperbolas in the feature space. The degree of membership of a vector z to a class q is defined as

$$\mu_q(z) = 1 - \frac{1}{n}\sum_{i=1}^{n} | z_i - w_{qi} |, \quad (15)$$

where w_q is the center of the hypersphere. This form of the membership function provides high resistance to local data perturbations, since the classification does not depend on individual components, but on the generalized deviation. In the tasks of inspection of renewable energy facilities, this is especially important, since real data often contain noise caused by atmospheric conditions, platform instability, or sensor artifacts. In addition, Fuzzy BSB demonstrates the lowest processing time among the considered methods, which makes it appropriate for real-time application.

The third component is the modified Wang–Mendel method, which is used as an expert-explanatory classifier [28]. It is based on the automatic formation of a database of fuzzy IF–THEN rules from training data. For each class, a rule is formed

$$R_k\text{: IF } z_1 \text{ is } A_1^k \wedge \cdots \wedge z_n \text{ is } A_n^k \text{ THEN class } C_k,$$

where A_i^k are fuzzy sets described by membership functions. The strength of the rule is defined as

$$\omega_k = \prod_{i=1}^{n} \mu_{A_i^k}(z_i). \quad (17)$$

The decision is formed according to the principle of maximum rule activity. The advantage of this approach is high interpretability: each decision can be explained in the form of a text description of the activated rules. This is especially important for critical infrastructure monitoring tasks, where the operator must understand the logic of automated conclusions.

The interaction of the considered classifiers is implemented within a cascade architecture with adaptive switching logic. The primary classification is performed by the hyper-sector FLVQ, after which additional indicators of the stability of the solution are calculated. The confidence level

$$Conf = \frac{\mu_{max} - \mu_{second}}{\mu_{max}}, \quad (18)$$

and the entropy of the membership distribution

$$H = -\sum_k p_k \log p_k. \quad (19)$$

Based on these parameters, an integral trust function is formed:

$$C = w_1 Conf + w_2(1 - H) - w_3 N, \quad (20)$$

where N is the feature noise estimate. The weighting coefficients in the trust function are selected based on validation experiments and normalized to ensure stability of the decision-making process. In the baseline configuration, equal weights are assigned to the confidence and entropy components, while further adjustment is performed depending on the level of noise and the degree of class overlap. Such a strategy ensures a balanced contribution of reliability and uncertainty measures in the final decision. This approach allows adapting the decision-making process to varying operating conditions without increasing computational complexity. If the value C below the set threshold, the system activates an auxiliary classifier: Fuzzy BSB in case of high noise or the Wang–Mendel method when classes overlap and an explanation is needed.

In terms of computational complexity, all the considered methods work with a compact feature space, so their complexity is $O(mK)$, where m is the dimension of the features, K is the number of classes. This provides the possibility of their implementation on embedded platforms. In addition, the combination of methods allows to compensate for the limitations of each of them: FLVQ provides accuracy, FBSB - robustness, and Wang–Mendel - explainability.

V. PROPOSED CASCADE ARCHITECTURE OF AN INTELLIGENT SYSTEM

The algorithm of the proposed intelligent system implements step-by-step processing of the data stream and reflects the logic of the cascade architecture. At the first stage, synchronized data collection from sensors is performed. At each point in time, the system receives an image or video frame, coordinates, platform orientation and additional parameters that form the input information package. After that, pre-processing is performed, which includes stabilization, brightness normalization, selection of the region of interest and scaling.

In the second stage, a compact feature space is formed. The modified convolutional network transforms the image into a feature vector z, which is a generalized description of the object state. Then this vector is fed to a hypersector classifier based on FLVQ, where the primary class of the defect is determined and the degree of membership in each class is calculated. The result is a pair (k, μ_k), where k – a specific class, μ_k – level of confidence.

After the initial classification, the algorithm proceeds to the stage of evaluating the stability of the solution. For this, the confidence level, entropy of the membership distribution and integral trust indicator are calculated (see equations (18) - (20)). If the value C (of equation (20)) exceeds the set threshold, the solution is considered stable and is transmitted to the system output.

If the stability is insufficient, the algorithm switches to the refinement mode. In the case of a high noise level, the Fuzzy BSB module is activated, which performs reclassification taking into account the associative structure of the data. If the uncertainty is associated with class overlap or the need for interpretation, the modified Wang–Mendel method is activated, which forms the base of activated fuzzy rules. After receiving the results, the reconciliation stage is performed, at which the final decision is formed according to the principle of maximum confidence or weighted voting.

The final stage of the algorithm is to generate a diagnostic package that includes the defect class, confidence level, localization coordinates, timestamp, and, if necessary, an image-proof. In the case of photovoltaic systems, a thermal anomaly map can be additionally generated, and for wind turbine blades, a spatial damage profile.

From the point of view of computational efficiency, the algorithm is conditionally iterative, since the auxiliary modules are activated only for a part of the data. The average processing time is defined as

$$T_{avg} = T_{base} + pT_{expert}, \quad (21)$$

where p – the probability of activating an additional module (auxiliary classifiers in the cascade structure, specifically the Fuzzy BSB or Wang–Mendel module). In practical conditions, this value is small, which ensures the possibility of implementing the system in real time.

The proposed intelligent system for classifying defects in renewable energy facilities is built in the form of a multi-level cascade architecture, which provides step-by-step data processing from the initial sensor signal to the final diagnostic solution. This approach was chosen taking into account the limitations of real operating conditions, in particular the need to work in real time, limited computing resources of on-board systems and high requirements for the reliability and explainability of results. Unlike monolithic models, the cascade structure allows for adaptively combining several intelligent modules, minimizing the average processing time and simultaneously increasing the accuracy of classification.

The choice of a cascade architecture is motivated by the need to balance accuracy and computational efficiency in real-time operation. Unlike monolithic deep neural networks, which process all data with the same complexity, the cascade structure enables selective activation of computational modules depending on the confidence of intermediate decisions. This significantly reduces the average processing time while preserving high classification performance.

Architecturally, the system implements a sequence of computational levels: sensor level, preprocessing level, compact feature space formation level, primary classification level, switching logic level, expert processing level, and results integration level (Fig. 1).

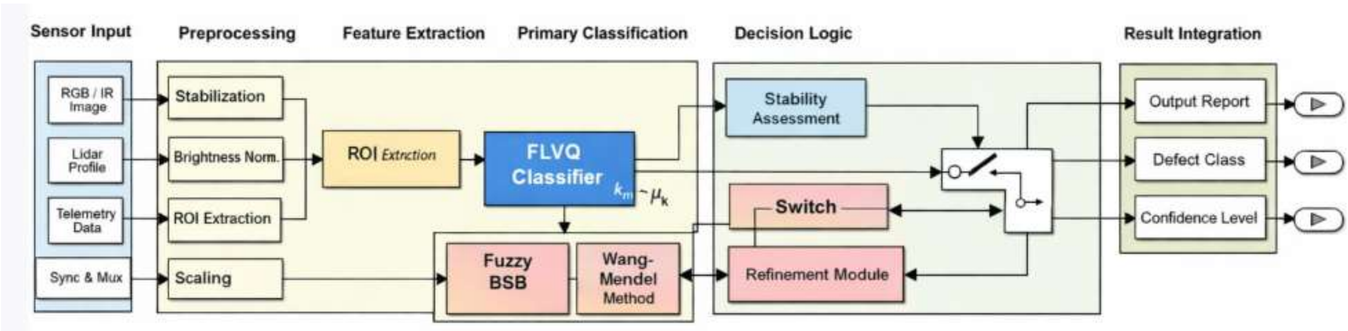

Figure 1 – Cascade system architecture

At the sensor level, a stream of input data is generated in the form of RGB images, thermal images, laser profiles and telemetry parameters. This data is synchronized by timestamps and coordinates, which ensures correct spatial localization of defects. Then, pre-processing is performed, which includes frame stabilization, brightness correction, region of interest selection, noise removal and data normalization, which allows minimizing the influence of external factors.

The next level is the formation of a compact feature space, where a modified convolutional neural network transforms each frame or its fragment into a low-dimensional feature vector. This representation is universal for all subsequent classification modules and allows you to significantly reduce computational costs. After that, the data is transferred to the primary classification level, where the hypersector method based on FLVQ is used, which provides fast decision-making with high accuracy in most cases. In addition to the defect class, this module forms additional characteristics, in particular, the confidence level, the distance to the hypersector boundary, and the distribution of membership in alternative classes.

The obtained indicators are transferred to the switching logic block, which determines the further processing route. If the solution of the primary classifier is sufficiently stable, the system generates the final result without additional calculations. Otherwise, auxiliary modules are activated - Fuzzy BSB or the modified Wang–Mendel method. The first is used in situations of increased noise or instability of features, as it provides robust classification, the second - in cases of overlapping classes or the need for explainability of the solution. After additional processing, the results are agreed using a weighted voting mechanism or confidence maximization.

From a theoretical point of view, the cascade architecture can be interpreted as a conditional ensemble of experts, where the choice of model depends on the characteristics of the input data. This approach allows to minimize the expected risk of errors:

$$R_{cascade} = \sum_i p_i R_i, \quad (22)$$

where R_i – risk of error of the corresponding module, p_i – the probability of its activation [29]. Thanks to this, the system maintains a balance between accuracy and speed even when operating in real time.

From a practical implementation perspective, the proposed architecture is easily scalable and can be implemented as a microservice structure, where each module functions independently. This allows for upgrading individual components without changing the entire system, and also provides integration with SCADA and other information monitoring platforms [30, 31].

In contrast to end-to-end deep learning models, which require significant computational resources and large training datasets, the proposed cascade approach provides a more flexible and resource-efficient solution. This is particularly important for embedded systems and edge devices, where computational and energy constraints are critical factors.

VI. EXPERIMENTAL RESULTS

Experimental testing of the proposed intelligent system was carried out to assess its effectiveness in the tasks of automated diagnostics of defects in renewable energy facilities, in particular wind turbine blades and photovoltaic panels. The research was conducted on a combined dataset formed from UAV images (RGB and thermal) obtained under different operating conditions, as well as from open datasets of renewable energy defects. The dataset includes: (i) a proprietary UAV dataset collected during field inspections of wind turbine blades using RGB and thermal cameras (approximately 1000 images); (ii) publicly available datasets, including [32]. All images were manually annotated by experts. Cross-validation was performed, but cross-dataset validation was not considered and remains part of future work.The sample included samples of four main classes of states: normal state, surface erosion, cracks and corrosion damage. In total, several thousand image fragments were used, which were pre-marked by experts. From the practical point of view, these defect classes can be ranked according to their criticality level. Cracks are considered the most critical defects due to their direct impact on structural integrity and risk of sudden failure. Corrosion represents progressive degradation that affects long-term reliability. Erosion leads to performance losses, primarily reducing aerodynamic or energy conversion efficiency. The normal state corresponds to a fully operational condition and serves as a reference baseline. Such ranking is important for intelligent monitoring systems, as it allows prioritizing maintenance actions and interpreting classification results in terms of risk.

To ensure the correctness of the assessment, a standard procedure was used to divide the data into training, validation, and test samples in the ratio of 60:20:20. The model was trained using cross-validation, which reduced the risk of overtraining. During the experiments, the main indicators were analyzed: classification accuracy (Accuracy), processing time of one frame (Time), as well as additional metrics - Precision, Recall, and F1-measure [33, 34].

The results of experimental studies have shown that the proposed hybrid cascade system provides consistently high values of classification accuracy (Accuracy over 94% on the test sample), exceeding individual neuro-fuzzy and classical ML approaches. The achieved level of accuracy is explained by the combination of a compact feature space and a cascade organization of classification, which allows minimizing class overlap and reducing the influence of noise on decision-making.

A more detailed analysis of the metrics showed that Precision and Recall demonstrate balanced values for all classes, indicating the absence of significant classification bias (Fig. 2). For the “normal state” class, the Precision and Recall values exceed 0.95, which confirms the efficiency of separating defective and non-defective samples. For the “erosion” and “corrosion” classes, the indicators are somewhat lower (in the range of 0.90–0.93), which is explained by the similarity of their textural characteristics and partial overlap in a compact feature space. At the same time, the F1-measure values remain high for all classes, which confirms the overall stability of the system.

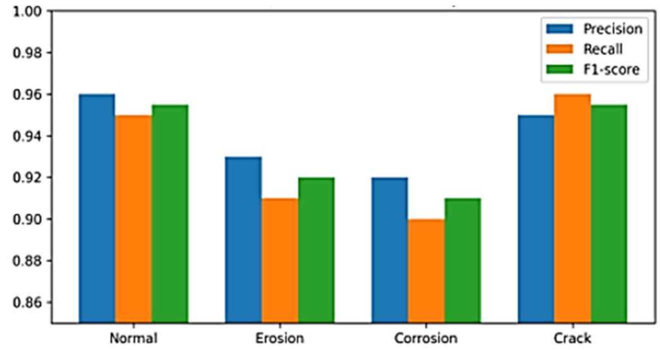

Figure 2. Precision, Recall and F1-measure values for each defect class

Analysis of the matrix (Fig. 3) of discrepancies showed that the main errors occur between the classes “erosion” and “corrosion” [35, 36]. This is explained by the fact that both types of defects have similar morphological features, such as local texture heterogeneity, changes in surface brightness and structural microdamage. In a compact feature space, these classes form partially overlapping regions, which makes their separation difficult even for complex models. At the same time, the cascade architecture allows to reduce the number of such errors by activating expert modules in cases of high uncertainty.

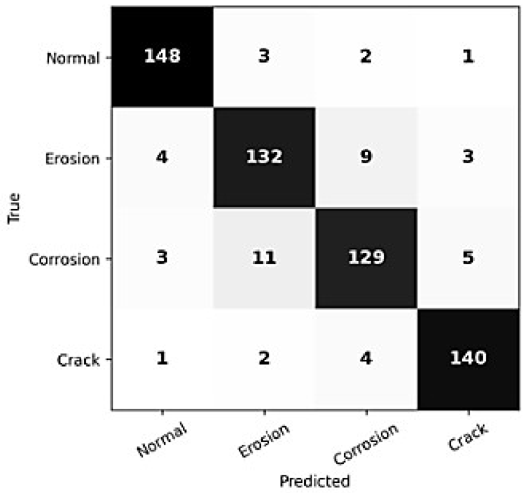

Figure 3. Discrepancy matrix of the proposed cascaded neuro-fuzzy system

The processing time for one frame was, on average, less than 0.15 s, which confirms the possibility of using the system in real time. The processing time was measured in a simulated environment, Google Colab, using a workstation equipped with [CPU/GPU specification]. The architecture has not yet been fully deployed on an embedded platform, which is planned as future work.

The results obtained confirm that the proposed approach provides not only high classification accuracy but also stability of results under different operating conditions, which is critically important for the practical application of renewable energy facility monitoring systems.

The experimental results obtained confirm the feasibility of using a hybrid cascade architecture for intelligent diagnostics of defects in renewable energy facilities. The combination of a compact feature space with neuro-fuzzy classifiers allowed for achieving high accuracy with significantly lower resource costs compared to deep CNN approaches. The system must demonstrate stable operation in conditions of limited data, which is typical for practical inspection tasks.

The cascade organization of the system has proven its effectiveness due to the adaptive distribution of the computational load. The basic classifier provides fast decision-making in most cases, while auxiliary modules are activated only when necessary. This allows for reducing the average processing time without losing accuracy. In addition, the use of neuro-fuzzy models provides an additional advantage in the form of explainability of decisions, which is important for practical implementation in critical infrastructure monitoring systems.

Unlike the approaches discussed above, the proposed cascade architecture combines the advantages of different classes of models: a compact feature space provides low resource consumption, the FLVQ classifier provides high accuracy, the Fuzzy BSB provides robustness to noise, and the Wang–Mendel method provides explainability of results. The comparison is based on reported results from the literature rather than direct reimplementation. All methods were evaluated under their original experimental conditions, and therefore, the comparison should be interpreted as indicative rather than strictly benchmarked. This allows us to achieve an optimal balance between accuracy, speed, and interpretability.

Table 1 – Comparison with modern analogues

Method	Type of approach	Data	Accuracy / mAP	Speedy	Interpretability
Mask R-CNN + fuzzy voting [9]	DL + FL	UAV RGB	mAP ≈ 80.1%	average	Medium
YOLO / ViT-based DL [20]	DL	UAV RGB	up to 97.8%	high	Low
ANFIS (adaptive) [10]	Neuro-fuzzy	UAV RGB	≈ 91%	high	High
Multispectral FIS [11]	Fuzzy	UAV multi	High	average	High
HOG+SVM+Gabor [21]	ML	RGB	≈ 92%	high	Medium
Proposed system	Hybrid cascade	UAV multi	**≈ 94%+**	high	High

The analysis shows that DL architectures provide the highest accuracy, but have significant resource limitations. Fuzzy systems are more explainable and stable to uncertainties, but are inferior in discriminative ability. Classical ML methods demonstrate limited effectiveness in complex conditions. In this context, the proposed hybrid cascade architecture provides the most balanced solution, combining the advantages of different approaches and demonstrating high efficiency in real conditions of UAV inspection of renewable energy facilities.

To provide a deeper interpretation of the obtained results, a dedicated discussion of limitations and future directions is presented below.

VII. DISCUSSION

From a methodological perspective, the use of cascade architecture may appear less common in modern image analysis dominated by deep learning models. However, in the context of intelligent monitoring systems operating under uncertainty and resource constraints, cascade structures provide a justified and effective alternative. Their ability to combine multiple models with different properties (accuracy, robustness, explainability) makes them particularly suitable for engineering applications.

The obtained results confirm that the proposed cascade neuro-fuzzy architecture provides a balanced combination of classification accuracy, computational efficiency, and interpretability. In contrast to purely deep learning approaches, the system is capable of operating under limited data conditions and can be implemented on resource-constrained platforms, which is critical for UAV-based monitoring applications.

At the same time, several limitations of the proposed approach should be noted. First, the classification of defects with similar morphological and textural characteristics, such as erosion and corrosion, remains a challenging task due to partial overlap in the compact feature space. Second, the effectiveness of the system depends on the quality of the feature extraction stage, which may be sensitive to environmental conditions such as lighting variations, sensor noise, and imaging angle. Third, the current model operates on frame-level analysis and does not explicitly incorporate temporal information about defect evolution.

Despite these limitations, the cascade architecture demonstrates significant advantages. The adaptive switching mechanism reduces unnecessary computational load by activating additional classifiers only in uncertain cases. Furthermore, the use of neuro-fuzzy models ensures the explainability of decisions, which is particularly important for technical diagnostics and integration into engineering decision-support systems.

Future research directions include the integration of multispectral data sources, the incorporation of temporal analysis for tracking degradation dynamics, and further optimization of the switching mechanism. In addition, the implementation of the system on edge platforms and its adaptation to real industrial operating conditions is promising.

VIII. CONCLUSIONS

The paper proposes a hybrid cascade neuro-fuzzy system for classifying defects in renewable energy facilities, which combines a compact feature representation, the speed of the primary classifier and the robustness of expert modules. Architecturally, the system implements a sequence of computational levels from sensor collection and preprocessing to integration of results and can be interpreted as a conditional ensemble of experts with adaptive switching logic depending on the characteristics of the input data.

Experimental studies have shown that the proposed approach provides consistently high Accuracy values (over 94% on the test sample) and balanced Precision and Recall indicators for all classes, which confirms the absence of significant classification bias. Analysis of the discrepancy matrix showed that the main errors occur between the “erosion” and “corrosion” classes, which is due to the similarity of their morphological and textural characteristics. At the same time, the cascade organization allows for reducing the number of such errors by activating expert modules in cases of increased uncertainty.

Comparison with existing analogues showed that the proposed system provides a more balanced ratio of accuracy, speed and interpretability of results compared to separate DL, ML and neuro-fuzzy approaches. The use of a compact feature space reduces computational costs, and the integration of FLVQ, Fuzzy BSB and the Wang–Mendel method increases noise resistance and ensures explainability of solutions. The results obtained confirm the practical feasibility of using the proposed system for automated monitoring of the technical condition of RES facilities.

Prospects for further research include expanding multispectral features, improving adaptive switching mechanisms, integrating the system into real-time edge environments, and testing on larger industrial samples.

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