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INTELLIGENT SYSTEM FOR REAL-TIME DETECTION AND CLASSIFICATION OF SOLAR PANEL DEFECTS

*The **subject matter** of the study in the article involves the process of detecting and classifying defects in solar panels in real-time using unmanned aerial vehicles (UAV) and artificial intelligence technologies. The **goal** of this study is to develop an intelligent system that combines an active monitoring methodology with Fuzzy BSB-based model for real-time detection and classification of solar panel defects. This will allow for the timely detection of defects and reduce the costs of repairing or replacing solar panels. The **tasks** to be solved are: to develop a method for active monitoring of the condition of panels based on laser scanning; to integrate algorithms for data processing and classification of defects in real time; to investigate the application of the Fuzzy BSB (Braine-State-in-the-Box) model to increase the stability of classification under conditions of noise and incomplete data. The methods used are: active laser scanning from UAVs, fuzzy neural network algorithms, the Fuzzy BSB associative memory model, as well as methods for analyzing images and feature vectors. The following **results** were obtained. A methodology for detecting defects at the transportation stage and during the operation of solar panels is proposed. A Fuzzy BSB model is proposed for classifying detected defects, which is capable of providing an accuracy of about 80% even under conditions of significant noise and class overlap. It is found that the system effectively distinguishes the main types of defects, in particular cracks, contamination, shading, and mechanical damage, demonstrating competitive advantages compared to traditional passive methods. **Conclusions.** The scientific novelty of the results obtained is as follows: 1) adapting the combination of associative memory and fuzzy logic in the Fuzzy BSB model to the classification of solar panel defects, which allows to increase the reliability of this classification in conditions of incomplete or noisy data; 2) the concept of integrating active laser scanning with intelligent analysis algorithms is proposed, which opens up prospects for creating flexible and adaptive systems for monitoring the condition of solar power plants.*

Keywords: *solar panels; defects; laser scanning; unmanned aerial vehicles; neural networks; intelligent system; Fuzzy BSB.*

1. Introduction

1.1. Motivation

Solar panels, or photovoltaic modules, play a key role in modern energy, as they allow direct conversion of solar radiation into electrical energy through the operation of photovoltaic cells made of silicon or other materials. Their use is an important factor in the transition to clean energy, as they reduce dependence on fossil fuels and reduce greenhouse gas emissions, which is confirmed by studies on the role of renewable technologies in combating climate change [1]. In addition, they ensure energy independence at the household and enterprise level, as they provide the opportunity to produce their own electricity and reduce the impact of energy crises. The economic benefit of using solar panels is manifested in reducing electricity costs and the ability to sell surpluses in countries with a green tariff system. Also, the development of solar energy infrastructure creates additional jobs and stimulates the development of related industries [2]. An important advantage is the flexibility of panel placement, as they can be installed on roofs, facades, or open areas, which allows for efficient use of available space.

However, the efficiency of solar panels has certain limitations. Their operation depends on weather conditions and light intensity, which reduces electricity production in winter or during cloudy weather. The tilt angle and orientation of the modules relative to the cardinal points have a significant impact, as well as temperature, which in case of overheating can cause degradation of performance [3]. The energy efficiency of solar power plants largely depends on the condition of

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their panels, which requires their appropriate maintenance. At the same time, panel defects can be both catastrophic (causing panel inoperability) and minor, which simply reduce the energy efficiency of the panels). Defects can be the result of damage or a consequence of normal operation (dust, fallen leaves). Thus, the problem of developing effective methods for detecting defects in solar panels arises. An analysis of existing works on the study of the problem has shown the importance of developing fast and reliable methods for detecting defects in solar energy facilities and classifying them using UAVs [4-6].

Known diagnostic methods are based on passive information collection, which requires high-quality equipment and significant amounts of data for training models. Therefore, the development of active control methods using laser scanning and intelligent data analysis is relevant. For this, the authors propose an approach based on the use of laser scanning using UAVs, as well as a method for classifying defects in solar panels based on a fuzzy neural network.

Diagnostics of photovoltaic module defects is critical to maintaining the performance and reliability of solar power plants. Traditional approaches include electroluminescent and infrared imaging, current-voltage characteristics analysis, and modern computer vision algorithms. However, real-world operating conditions such as variable illumination, temperature effects, surface contamination, and module heterogeneity introduce significant uncertainty and noise.

The goal of this study is to develop an intelligent system that combines an active monitoring methodology with a Fuzzy BSB-based model for the real-time detection and classification of solar panel defects.

1.2. State of the art

As the number of solar power plants increases [7], there is a need for automated monitoring systems to detect and localize solar panel faults. The performance reduction can reach 50%, making early diagnosis critically important. The paper [8] analyzes a photovoltaic panel monitoring system for shading and fault detection using artificial neural networks (ANNs) and the Internet of Things (IoT). The main method is to use ANNs to model complex interactions between input and output data, which allows for accurate prediction of ideal panel performance and prompt detection of shading or other defects. IoT provides remote real-time monitoring, which reduces maintenance costs by timely detection and localization of problems. The advantages of this approach are high accuracy, adaptability, and reduced energy losses, but the system requires constant model updates and may therefore be dependent on an Internet connection.

The article [9] is devoted to localization of hot spots on solar panels and classification of their faults using deep learning methods. Thermographic images taken by an infrared camera and two architectural solutions based on deep learning networks ResNet-50 and Faster R-CNN were used to detect faults. The proposed system allows to automate the fault detection process, which reduces the need for manual inspection, but requires a large sample for training the neural network and does not classify mechanical damage to solar panels.

In [10], a photovoltaic panel monitoring system using ANN and IoT is considered. ANNs are used to accurately detect shading and other faults by modeling the interaction between input and output data, which allows predicting panel performance. The advantages of the approach are high accuracy and adaptability of the model. IoT provides real-time remote monitoring, allowing for timely detection of faults and reducing maintenance costs, although there is a dependence on the Internet connection and security issues. To optimize the operation, the "Perturb and Observe" method was used, which adjusts the panel parameters to achieve maximum power. This approach is simple and effective, although it may have temporary energy losses during sudden changes in illumination. It also requires frequent updating of the models to take into account new conditions.

Panel fault detection methods [11-14] use artificial intelligence to process images. Infrared thermography allows for non-contact defect detection and provides rapid detection, but accuracy depends on the quality of the camera and the operator's experience. Electroluminescent testing, which uses infrared images to detect cracks and damage, uses deep learning models to automate the diagnostic process. Deep learning algorithms, CNN and Faster RCNN, provide high efficiency and accuracy in defect detection, but require large amounts of data for training, require sophisticated equipment and expert support [15-17].

The article [18] describes methods for detecting and diagnosing faults in solar power plants based on artificial intelligence algorithms for high accuracy of defect detection. In addition, the use of fuzzy logic and decision trees provides high-accuracy classification of faults, but requires significant expert training for tuning. The main disadvantage is the need for a large amount of data and memory for the functioning of the algorithms.

A review of recent imaging work shows the rapid progress of deep models for module-level defect detection and segmentation, in particular variants of VarifocalNet class detectors, which increase accuracy and speed on visible images. At the same time, these methods require large labeled databases and controlled shooting conditions [19]. This creates space for alternatives that can work with scan-sensor features and partially distorted input vectors without losing interpretability. Such approaches include the fuzzy associative memory Fuzzy BSB (Brain-State-in-a-Box), which combines the dynamics of standard recovery with fuzzy membership measures.

At the level of formal decision-making systems in photovoltaic installations, fuzzy logic is widely used for classification of states and failures. Works on diagnostics of hot-spots by several electrical indicators demonstrate high accuracy even in field conditions, when fuzzy rules are properly designed. It is significant that with sufficient feature engineering, fuzzy systems achieve impressive metrics, however, unlike associative memory, they usually do not have a built-in “approximation” to the standard when the input data is partially lost or significantly noisy [20]. Fuzzy BSB here acts as a logical continuation: the model stores prototypes of defects and through iterative nonlinear dynamics delays observations to the nearest prototype. The fuzzy component allows you to additionally display the degrees of membership in cases of class intersection. Unlike purely visual pipelines, Fuzzy BSB organically works with aggregated sensory features, including laser scanning data, and provides a more transparent interpretation of the solution due to distances to prototypes and state changes during the convergence process. From the associative memory theory perspective, work with optimal and robust BSB/gBSB designs shows how the selection of the weight matrix, prototype normalization, and activation choice affect the size and homogeneity of the attraction regions, ensuring global stability and robustness to weight perturbations. These results directly support the engineering solutions used in Fuzzy BSB for defect classification.

Empirical studies of non-photo-visual features show that well-designed indicators, such as aggregates from local scan zones, scattering statistics or deviations from the profile, are able to form individual prototypical “portraits” of defects in the feature space. In this way, a trained Fuzzy BSB can combine high selectivity with attraction to standards, while remaining operational in the presence of noise, when, say, the parameters are partially undermeasured and the class boundaries are not sharp. When the data come from temperature-unstable regimes, standard memoryless fuzzy systems usually lose stability, while the associative dynamics of the BSB stabilize the classification [21].

The prototype of the proposed research is a multilayer deep learning model [22], which is used to detect and localize defects in solar panels. The advantages include high accuracy (up to 97%) and the ability to simultaneously detect and localize different types of defects, such as microcracks, erosion, and dust. The disadvantages are the complexity of implementation and the need for large computational resources for image processing and model training.

A common drawback of the considered methods is their passive nature. They do not use any active influences on the solar panels, and therefore have relatively low sensitivity and require high-quality equipment and significant amounts of data for training and defect recognition.

1.3. Objectives and tasks

This research aims to address the important scientific and applied problem of improving the operational safety, reliability and efficiency of solar power plants. This is achieved by developing an intelligent integrated monitoring and diagnostics system that provides rapid detection of panel defects, accurate classification of their causes and generation of recommendations for optimizing maintenance strategies.

To achieve this goal, the following main tasks are solved in the work:

1. Development of a comprehensive methodology for active data collection, based on the use of unmanned aerial vehicles equipped with video cameras and laser scanners, with subsequent combination of the results with sensor indicators of the energy characteristics of the panels, ensuring spatial resolution of about 1–2 mm per pixel and synchronization accuracy within 2–3 %.
2. Formation of an experimental dataset of solar panel defects and use of convolutional neural networks for automated detection and initial localization of damage, achieving an average processing time of approximately 0.5 s per frame.
3. Development of an intelligent classification model based on a Fuzzy BSB neural network, which provides high robustness of defect recognition in conditions of noise and incomplete measurements, maintaining classification accuracy close to 80 % and an F1-score of about 0.8 under cross-validation.
4. Building an integrated decision support system that combines classification results allows for rapid assessment of defect criticality and the provision of maintenance scenarios, reducing false defect detections by roughly 15–20 % compared with rule-based diagnostic approaches.

The paper is structured as follows. Section 1 provides an overview of current research and methods for monitoring the condition of solar panels.

Section 2 describes the data collection methodology, applied algorithms, and architecture of the proposed system.

Section 3 presents the results of experimental studies and their analysis.

Finally, Section 4 summarizes the conclusions and outlines the prospects for further research related to the

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improvement of the Fuzzy BSB model and its integration with modern deep learning methods.

2. Materials and methods of research

The methodology used in the study involves the application of artificial intelligence to detect and classify defects in solar panels at different stages of their life cycle. It is needed to provide fast and accurate damage detection using unmanned aerial vehicles (UAVs), followed by data analysis using the combination of neural networks and fuzzy logic.

When solar panels are manufactured, they undergo a full inspection of their efficiency parameters. However, during transportation and storage in a warehouse, defects sometimes occur that significantly affect their performance or energy efficiency. Known methods for detecting defects in solar panels are either quite complex and require complex and expensive specialized equipment, or have low reliability of results. A simple research method is proposed that provides high reliability, requires a minimum of equipment and can be implemented in warehouse conditions. To do this, the panels are scanned using a hand-held scanner that creates a narrow light strip on the panel. At the same time, voltage drops are measured at a load resistance close to the nominal resistance of the panel. The power of the generated energy is calculated from these voltage drops, and the impact of transport defects on the energy efficiency of the panel is indicated by the relative change in the output power of the panel during the action of the light strip. Since the measurements are relative, there is no need for high-precision equipment and special research conditions.

A similar method for examining solar panels is proposed to detect their defects during operation. The modification of the method consists in using a UAV to provide remote access to the panels and their scanning using a laser beam. The latter, due to the high energy efficiency of the laser beam, allows for relative measurements to be made during the study even in sunny weather. At the same time, it is proposed to achieve an increase in the accuracy of defect localization through joint intellectual processing of the results of measurement series in different directions of UAV movement.

In this study, the concept of active laser scanning for photovoltaic module inspection is considered at the methodological level. To ensure reproducibility and provide physical grounding of the proposed approach, the basic instrumental parameters of the conceptual setup are presented below. The laser source operates at a wavelength of λ = 650 nm with an output power of approximately 10 mW, forming a scanning stripe of 1.2 mm width and a scanning step of 0.5 mm. The data acquisition rate is 50 samples/s, which corresponds to the nominal scanning speed of 0.2 m/s.

For the classification of solar panel defects, an intelligent joint processing of detailed local images of localized defect zones and energy spectra of output voltage and current obtained from UAVs is proposed. This processing for the detection and localization of solar panel defects is proposed to be carried out on the basis of convolutional neural networks, the result of which will be a number of defect feature vectors in the image.

Initially, data is collected using UAVs that photograph solar panels. These images are transmitted to a fuzzy neural network for further analysis and fault detection. The resulting images are stored on cloud services or local servers with high power, adhering to standards for easy access. A convolutional neural network processes such images and forms a feature vector for each of them. A fuzzy neural network uses this data to quickly classify panel defects in real time. After that, the information can be used for further research or model improvement. Classification of solar panel defects is proposed to be carried out using a fuzzy neural network, which processes a set of feature vectors online and is trained on a small sample, unlike classical neural networks used for this class of tasks. The analyzed defect categories in this research are cracks, shading, soiling, and mechanical damage. They were chosen as they represent over 95% of real-world PV module failures [8, 9]. Each defect alters the reflected laser profile and power response in specific ways, forming distinct clusters in the feature space processed by the Fuzzy BSB classifier. A fuzzy neural network guarantees high accuracy of analysis, which allows for rapid fault detection and improved monitoring of solar panels.

The general scheme of the proposed system is shown in Figure 1.

The proposed intelligent system integrates unmanned aerial vehicles (UAVs) equipped with active and passive sensors and a ground-based computing environment that performs neural-network data processing. The UAV subsystem consists of four functional modules: a localization tool for stabilizing the drone position and maintaining the correct scanning trajectory; a main sensor (video camera) that captures visual data of the solar panels; a main actuator (laser radiation unit) that performs active surface scanning and generates reflected signals for subsequent analysis; and an energy-measuring device that records the electrical response of the panels during laser illumination. All incoming sensor streams are pre-processed in real time by a mini-computer installed onboard the UAV, which performs primary noise filtering, coordinate alignment, and packet formation. The processed data are then transmitted via a radio channel to the computing environment on the ground station.

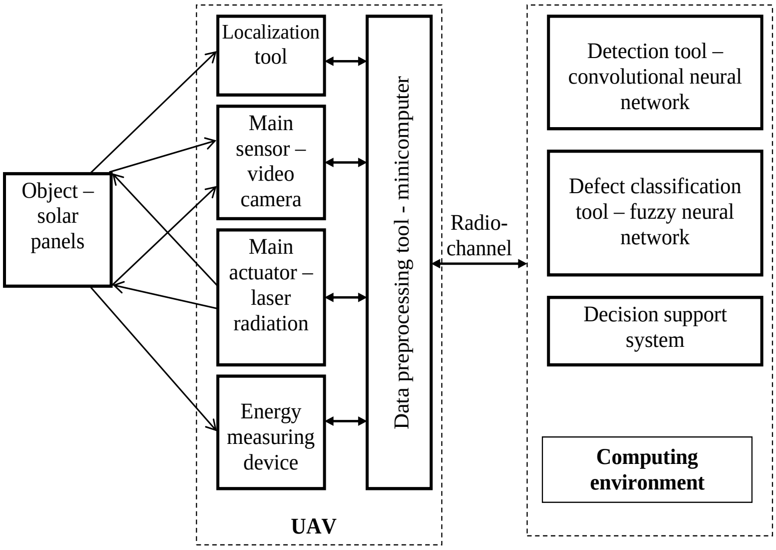

Fig. 1. General structure of solar panel defect detection

The computing environment includes three interconnected intelligent modules. The detection tool, implemented as a convolutional neural network (CNN), automatically identifies and localizes potential defects on image frames, forming feature maps that reflect shading, cracks, contamination, or surface deformation. The extracted features are then analyzed by the defect classification tool, which uses a fuzzy associative neural network of the Fuzzy BSB type. This model combines associative memory dynamics with fuzzy membership logic, allowing stable classification even in the presence of noise or incomplete measurements. Finally, the decision-support system aggregates the classification outputs, evaluates the criticality of the detected defects, and generates maintenance recommendations for operators in near-real-time mode.

The system operates in two primary modes: inspection mode (during which the UAV performs autonomous flight, laser scanning, and video data acquisition under real illumination conditions) and analytical mode (the computing environment processes the transmitted data through the CNN–Fuzzy BSB pipeline and makes the classification decision).

The computing environment contains a tool for classifying defects in solar panels. It is proposed to use Fuzzy BSB [22, 23] for data processing.

Fuzzy BSB (Brain-State-in-a-Box) combines the properties of associative memory with fuzzy clustering mechanisms, allowing data to be restored and classified even in the presence of partial information loss or noise. Due to its construction based on a hypercube and the ability to form fuzzy membership functions, the Fuzzy BSB model has high stability, generalization ability, and adaptive learning, which makes it promising for forecasting and monitoring tasks in photovoltaic installations.

To use the BSB model, all data are normalized to the range [-1; 1], which allows us to place vectors in the hypercube spaces accordingly:

$$\begin{cases} x_{min} \le x \le x_{max} \\ -1 \le \tilde{x} \le 1 \end{cases}, \qquad (1)$$

where x_{min} is the smallest value of the input variable, x_{max} is the largest value of the input variable, $\tilde{x} = a + bx$ is the encoded value of the input variable.

From here

$$\begin{aligned} x_{min} &\to -1 = a + bx_{min}, \\ x_{max} &\to 1 = a + bx_{max}. \end{aligned} \qquad (2)$$

Let's find the coefficients a and b:

$$\begin{gathered} a = 1 - bx_{max} \\ -1 = 1 - bx_{max} + bx_{min} \\ -2 = b(x_{min} - x_{max}) \\ 2 = b(x_{max} - x_{min}) \end{gathered}$$

Hence, $b = \dfrac{2}{x_{max} - x_{min}}$ and therefore

$$\begin{aligned} a &= 1 - \frac{2x_{max}}{x_{max} - x_{min}} = \frac{x_{max} - x_{min} - 2x_{max}}{x_{max} - x_{min}} = \\ &= \frac{-x_{max} - x_{min}}{x_{max} - x_{min}} = \frac{-(x_{max} + x_{min})}{x_{max} - x_{min}} = \frac{x_{max} + x_{min}}{x_{min} - x_{max}}. \end{aligned} \qquad (3)$$

Therefore, the encoding of the value of the input variables into the interval [-1;1] occurs as follows:

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$$\tilde{x} = \frac{x_{max} + x_{min}}{x_{min} - x_{max}} + \frac{2x}{x_{max} - x_{min}} = \\ = \frac{x_{max} + x_{min}}{x_{min} - x_{max}} - \frac{2x}{x_{min} - x_{max}} = \\ = \frac{x_{max} + x_{min} - 2x}{x_{min} - x_{max}}. \quad (4)$$

Let $\tilde{x}^k \in R^n$ be the input feature vector at iteration k, where n = 5 (which corresponds to the investigated number of classes of defects of solar panels). The network state is updated according to the rule:

$$\tilde{x}^{(k+1)} = \psi(\tilde{x}^{(k)} + \alpha \cdot W \cdot \tilde{x}^{(k)}), \quad (5)$$

where $\alpha > 0$ is the feedback coefficient, W is the $(n \times n)$ weight matrix, and $\psi(\cdot)$ is the piecewise linear activation function with saturation for the output variable y:

$$\psi(y_i) = \begin{cases} 1, \text{ if } y_i > 1 \\ y_i, \text{ if } -1 < y_i < 1. \\ -1, \text{ if } y_i < -1 \end{cases} \quad (6)$$

Although the classical BSB model operates in an n-dimensional hypercube with 2^n possible vertex states, in the this research, the system stores only five fuzzy prototype vectors corresponding to the identified defect types: normal, cracks, shading, contamination, and mechanical damage. Each prototype is associated with one class center in the feature space, and the hypercube formalism is used solely to define the distance metric and membership degree within this bounded state space. Thus, the number of functional clusters equals the number of defect classes (five), while the theoretical 2^n vertices serve as a continuous representation domain for associative convergence.

The BSB fuzzy model takes into account the distance between the current input and the vertices of the hypercube to calculate the membership function:

$$\mu_q(\tilde{x}) = 1 - \frac{1}{n}\sum_{i=1}^{n} \left| \tilde{x}_i - \tilde{x}_{qi} \right|, \quad (7)$$

where x_q is the q-th vertex of the hypercube.

The closer x is to the vertex, the larger the value of the membership function μ_q. This allows partial membership in multiple clusters and provides flexible classification.

The initial weights are calculated using Hebb's rule:

$$W = \sum_{k=1}^{l} \tilde{x}^{(k)} (\tilde{x}^{(k)})^T. \quad (8)$$

Further refinement of the weights is performed according to the Widrow-Hoff rule:

$$W^{(k+1)} = W^{(k)} + \eta(\tilde{x}^{(k)} - W^{(k)} \cdot \tilde{x}^{(k)}) \cdot (\tilde{x}^{(k)})^T, \quad (9)$$

where η is the learning rate.

After training, the predicted value $\hat{y}$ for a new input x is calculated as a weighted sum over the clusters:

$$\hat{y} = \sum_q \mu_q(\tilde{x}) \cdot y_q, \quad (10)$$

where y_q is the average output value, associated with cluster q.

3. Results and Discussion

The data for the experiment were obtained by laser scanning the surface of the solar panel. Each row in the data set corresponds to a separate scan point. To ensure representativeness and class balance, data from 155 real scan points were augmented with simulated samples based on variations in real parameters. The total training and testing sample size was 700 and 300 examples. The input variables describe the purity, centers of deviations and total signals across the four scan zones. The output variable is the real laser power (*Plaser real*), which is used as an indicator of the panel state. The Fuzzy BSB model, which combines associative memory and fuzzy classification mechanisms, was used to build the classifier.

The features of the variables well reflect typical defects: high or low values of the *centr* parameter signal surface curvature or the presence of cracks; low total indicators or a low *Plaser real* value may indicate shading, damage, or contamination. Classification labels were generated by a combination of *Plaser real*'s automatic threshold analysis and expert assessment of the panel condition. Power values below 80% of the reference were considered a sign of a defect.

Asymmetry between zones (for example, when the value for the first zone significantly exceeds the indicators of the third) indicates local structural violations. Negative center shifts can be interpreted as depressions, while positive ones can be interpreted as elevations or the presence of foreign objects on the surface. Shading was distinguished from soiling by the spatial extent and temporal persistence of the attenuation area: shading affected larger and stable regions, whereas soiling appeared as local and transient irregularities. The final labels were established through expert consensus, ensuring consistent and interpretable ground-truth categories for classification.

Figure 2 shows a graphical representation of the distribution of feature vectors across the studied defects of solar panels.

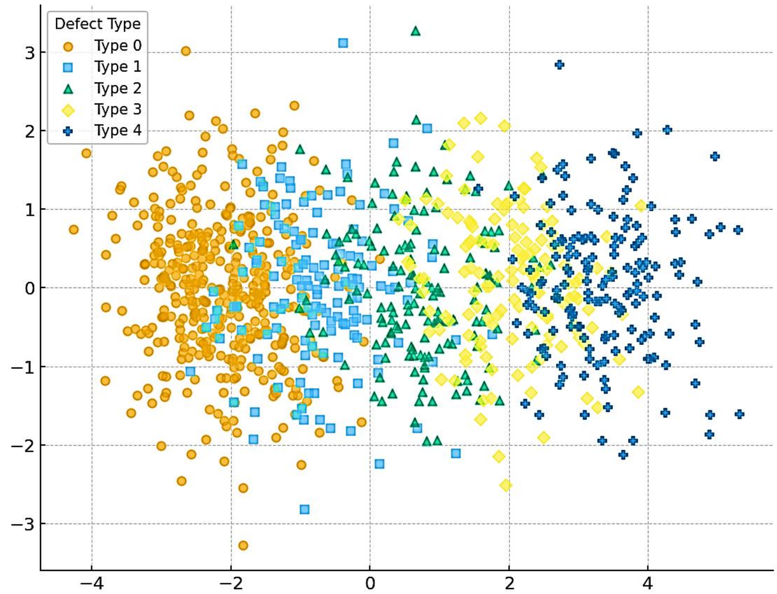

Fig. 2. Distribution of feature vectors of the studied defects of solar panels

To form the training sample, all features describing purity, centers of deviation and total zone values are usually taken, in total about eleven main parameters, which correspond to the cleaned data from 14 primary indicators. As a target variable, either the real laser power (*Plaser real*) can be used to predict quantitative values, or classification labels that reflect the type of defect.

The data studied investigated typical defects of solar panels that affect reflectivity and light transmission. Based on the interpretation of the variables and the experimental setup, the following categories can be distinguished:

0 Normal (no defect) – the panel is operating normally, the signal indicators are stable, the real laser power (*Plaser real*) is close to the expected one.

1 Cracks – manifest as sharp changes in the *centr* parameter, indicating surface curvature; asymmetries between measurement zones may also be observed.

2 Shading – characterized by a decrease in the total signals (*sum1,2*, *sum3,4*) and a drop in *Plaser real*; can be caused by dust, leaves, foreign objects, or partial overlap of the panel.

3 Contamination is similar to shading, but is more local in nature: individual zones give a much lower signal compared to others.

4 Mechanical damage (dents, scratches, surface deformations) - are displayed as persistent positive or negative center deviations (*centr*), indicating depressions or elevations on the panel surface.

These data can be considered as multi-channel measurements reflecting the state of the solar panel surface at different points. The difference between the ideal and actual laser power allows us to assess the degree of defect: the greater this difference, the greater the impact of the damage on the reflective properties of the panel and its energy efficiency.

Figure 3 shows the distribution of defect types in the real data.

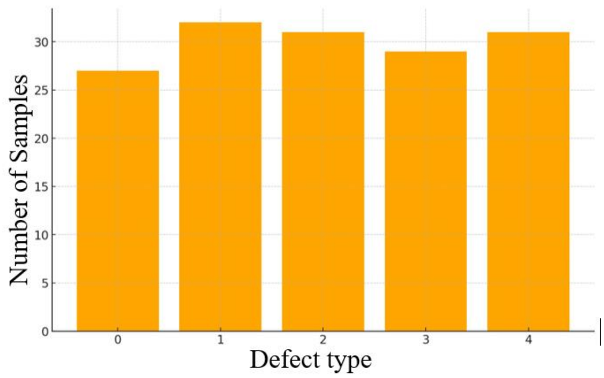

Fig. 3. Distribution of types of defects studied in solar panels

Thus, the investigated defects include both structural damage (cracks, warping, dents) and operational problems (shading, dirt, foreign objects). All of them directly affect the panel's power output and can lead to significant energy losses.

The model was tested on a subset of the data with a 70/30 split for training and testing. Figure 4 shows the confusion matrix of the training process, illustrating the classification quality.

The training sample shows that classes 1–4 are identified almost without error: the model correctly classifies 135 objects of class 1, 132 objects of class 2, 144 objects of class 3, and 150 objects of class 4. The main difficulties arise in class 0, where a significant "smearing" of predictions is observed: some objects were assigned to classes 1, 2, 3, and 4, and no example was

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classified as belonging to class 0. This indicates that the prototypes of class 0 in the feature space overlap with other classes, which makes their differentiation difficult.

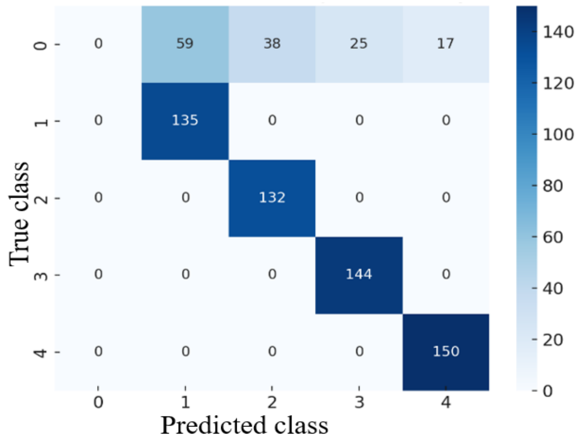

Fig. 4. Fuzzy BSB training data confusion matrix

The results on the test sample confirm this trend (Figure 5).

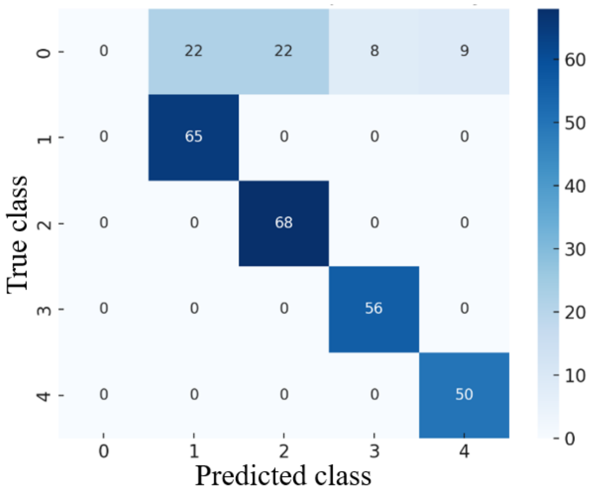

Fig. 5. Confusion matrix of Fuzzy BSB testing data

For classes 1–4, the model maintains high accuracy: all 65 examples of class 1, 68 examples of class 2, 56 examples of class 3, and 50 examples of class 4 are classified absolutely correctly. Class 0 again shows significant problems - no correct prediction, and all 61 examples were assigned to other categories, mainly classes 1 and 2. This indicates the difficulty of restoring the normal structure of type 0, i.e., without defect, by associative BSB dynamics.

The model was studied in the Matlab environment. As a result of the study, the average F1-score was 0.79. For class 0, the accuracy was lower due to the partial overlap of features with class 1. A sensitivity analysis of the model was performed with respect to the parameter α (in the range 0.2–0.8), which showed that optimal results are achieved at α = 0.5 and gain = 1.2. Moreover, to evaluate the stability and generalization ability of the developed Fuzzy BSB model, a five-fold cross-validation procedure was applied. The entire dataset was randomly divided into five equal subsets, where each subset was used once as a test set while the remaining four served for training. The average classification accuracy across all folds reached 79.7% with a standard deviation of ±2.3%, confirming the model's robustness and consistent performance on unseen data. Comparative experiments showed that the Fuzzy BSB classifier achieved an average F1-score of 0.79, which is 14% higher than the baseline nearest-prototype method and only 17% lower than deep CNN-based models (0.96 F1-score [22]). However, the proposed system requires 4× less training data and operates 2× faster in inference, making it more suitable for real-time UAV deployment.

The study makes some assumptions. For example, it is assumed that most defects occur during the transportation or storage of panels and are of a specific nature, such as cracks or dents. The use of relative stress measurements reduces the need for complex equipment, which simplifies the process.

One potential difficulty may be limited accuracy in adverse weather conditions. To solve this problem, laser scanning will be used, which increases the efficiency of analysis regardless of lighting. Another problem may be the difficulty in training neural networks on small samples. This problem is solved by using fuzzy neural networks, which require a smaller amount of data for training.

Compared to the passive methods described above, the proposed approach provides:

– work in most lighting conditions (the method is validated for diffuse daylight and moderate reflection levels);

– smaller requirements for the amount of training data;

– the ability to localize defects without stopping the panels.

The disadvantage of Fuzzy BSB is its lower classification accuracy compared to deep neural networks [22] (about 80% versus 97%). Limitations also include the dependence on the correct choice of parameters (α, gain) and relatively slow convergence in cases of high dimensionality of the data. These disadvantages can be overcome by:

– hybridization with deep neural networks, where Fuzzy BSB is used as a pre-filter or interpretation module;

– parameter optimization through evolutionary algorithms (e.g., genetic algorithms or particle swarm) to find the best values of α and gain;

– expanding the volume of training data using synthetic generation, which allows for increased classification accuracy;

– parallel implementation of BSB dynamics to speed up calculations.

Thus, Fuzzy BSB does not significantly lose to deep learning in accuracy, but is a valuable tool due to its reliability, simplicity, and ability to work in conditions of incomplete and noisy data.

4. Conclusions

The study considered the problem of reducing the efficiency of solar panels due to defects on their surface and proposed an intelligent system for their detection and classification using the Fuzzy BSB model. The main contribution of this study lies in developing an integrated real-time monitoring and classification system that combines active laser scanning with Fuzzy BSB. The approach provides explainable fuzzy reasoning and robustness under incomplete data. Parameters suitable for optimization include the feedback coefficient, activation gain, and prototype normalization factors, which directly influence convergence speed and classification stability. The results of experiments with laser scanning data confirmed that this approach is capable of providing a sufficiently high accuracy of defect classification even in the presence of noise and incomplete measurements. Comparison with the basic method of the closest prototype demonstrated that although the latter achieves ideal accuracy indicators, it does not take into account fuzzy membership and does not have generalization mechanisms. The Fuzzy BSB model showed an accuracy of approximately 80%, which indicates its practical suitability for monitoring tasks. The proposed intelligent system is promising due to the combination of associative memory and fuzzy logic, which provides transparency of decision-making, flexibility, and adaptability.

Future research will focus on optimizing model parameters and expanding the training dataset through evolutionary optimization methods, as well as integrating the Fuzzy BSB model with modern deep learning algorithms in a hybrid deep–fuzzy framework to further enhance accuracy, robustness, and the overall performance of the solar panel defect detection and classification system.

Contributions of authors: conceptualization and structure of solar panel defect detection – **Lesia Dubchak, Volodymyr Kochan;** formulation of tasks, analysis **– Lesia Dubchak, Anatoliy Sachenko;** development of mathematical model, software, verification **– Lesia Dubchak, Yevgeniy Bodyanskiy;** analysis of results, visualization **– Lesia Dubchak, Oleg Savenko;** final review and editing **– Anatoliy Sachenko, Oleg Savenko.**

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.

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References

1. Schulte, E., Scheller, F., Sloot, D., & Bruckner, T. A meta-analysis of residential PV adoption: the important role of perceived benefits, intentions and antecedents in solar energy acceptance. *Energy Research & Social Science*, 2022, vol. 84, article no. 102339. DOI: 10.1016/j.erss.2021.102339.

2. Lopushanska, M., & Ivanov, Ye. Klimatychni chynnyky ta yikhnya rol′ u rozvytku sonyachnoyi enerhetyky u L′vivs′kiy oblasti [Climate factors and their role in the solar energy development in the Lviv region]. *Ecological Sciences*, 2022, vol. 45, pp. 54–59. DOI: 10.32846/2306-9716/2022.eco.6-45.9. (In Ukrainian).

3. Sun, X., Silverman, T. J., Zhou, Z., Khan, M. R., Bermel, P., & Alam, M. A. Optics-Based Approach to Thermal Management of Photovoltaics: Selective-

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

Spectral and Radiative Cooling. *IEEE Journal of Photovoltaics*, 2017, vol. 7, no. 2, pp. 566-574. DOI: 10.1109/JPHOTOV.2016.2646062.

4. Al Dhafari, L. S., Afzal, A., Al Abri, O. K., & Khan, A. Solar-Powered UAVs: A systematic Literature Review. *Proc. 2nd Int. Conf. on Unmanned Vehicle Systems-Oman (UVS)*, Muscat, Oman, 2024, pp. 1-8. DOI: 10.1109/UVS59630.2024.10467158.

5. 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.

6. Hurin, A., Khudov, H., Kostyria , O., Maslenko, O. & Siadrystyi, S. Comparative analysis of spectral anomalies detection methods on images from on-board remote sensing systems. *Advanced Information Systems*, 2024, vol. 8, iss. 2, pp. 48–57. DOI: 10.20998/2522-9052.2024.2.06.

7. Tripathi, A., Gundebommu, S. L., Mishra, H., Shravani, C., Alwetaishi, M., Atamurotov, F., Benti, N. E., Sura, S., & Saleel C., A. Integration of Solar PV Panels in Electric Vehicle Charging Infrastructure: Benefits, Challenges, and Environmental Implications. *Energy Science & Engineering*, 2025, vol. 13, iss. 4, pp. 2135-2152. DOI: 10.1002/ese3.70014.

8. Venkatakrishnan, G. R., Rengaraj, R., Tamilselvi, S., Harshini, J., Sahoo, A., Saleel, C. A., Abbas, M., Cuce, E., Jazlyn, C., Shaik, S., Cuce, P. M., & Riffat, S. Detection, location, and diagnosis of different faults in large solar PV system—a review. *International Journal of Low-Carbon Technologies*, 2023, vol. 18, pp. 659–674. DOI: 10.1093/ijlct/ctad018.

9. Pathak, S. P., Patil, S., & Patel, S. Solar panel hotspot localization and fault classification using deep learning approach. *Procedia Computer Science*, 2022, vol. 204, pp. 698-705. DOI: 10.1016/j.procs.2022.08.084.

10. Abdallaha, F. S. M., Abdullaha, M. N., Musirinb, I., & Elshamyc, A. M.Intelligent solar panel monitoring system and shading detection using artificial neural networks. *Energy Reports*, 2023, vol. 9, sup. 10, pp. 324-334. DOI: 10.1016/j.egyr.2023.05.163.

11. El-Banby, G. M., Moawad, N. M., Abouzalm, B. A., Abouzaid, W. F., & Ramadan, E. A. Photovoltaic system fault detection techniques: a review. *Neural Computing and Applications*, 2023, vol. 35, pp. 24829-24842. DOI: 10.1007/s00521-023-09041-7.

12. Li, T., Hua, M., & Li, Q. Intelligent Inspection Method for Photovoltaic Modules Based on Image Processing and Deep Learning. *Advances in Artificial Intelligence, Big Data and Algorithms*. IOS Press, 2023, pp. 48-56, DOI: 10.3233/FAIA230791.

13. Ali Jallal, M., El Yassini, A., Chabaa, S., & Zeroual, A. Towards Smart Monitoring Systems: Fault Detection and Diagnosis-Based Artificial Intelligence Algorithms in Solar PV Power Plants. *Journal of Nano- and Electronic Physics*, 2022, vol. 14, no. 5, article no. 05004. DOI: 10.21272/jnep.14(5).05004.

14. Et-taleby, A., Chaibi, Y., Ayadi, N., Elkari, B., Benslimane, M., & Chalh, Z. Enhancing fault detection and classification in photovoltaic systems based on a hybrid approach using fuzzy logic algorithm and thermal image processing, *Scientific African*, 2025, vol. 28, article no. e02684. DOI: 10.1016/j.sciaf.2025.e02684.

15. Nassreddine, G., El Arid, A., Nassereddine, M., & Al Khatib, O. Fault Detection and Classification for Photovoltaic Panel System Using Machine Learning Techniques. *Applied AI Letters*, vol. 6, iss. 2, article no. e115. DOI: 10.1002/ail2.115.

16. Ghahremani, A., Adams, S. D., Norton, M., Khoo, S. Y., & Kouzani, A. Z. Advancements in AI-Driven detection and localisation of solar panel defects. *Advanced Engineering Informatics*, 2025, vol. 64, article no. 103104. DOI: 10.1016/j.aei.2024.103104.

17. Khudov, H., Makoveichuk, O., Khizhnyak, I., Varvarov, V., & Zots, F. Experimental studies of the image segmentation method quality from unmanned aerial vehicles based on the ant colony optimization algorithm under the influence of additive Gaussian noise. *Advanced Information Systems*, 2025, vol. 9, iss. 3, pp. 14-21. DOI: 10.20998/2522-9052.2025.3.02.

18. Jia, Y., Chen, G., & Zhao, L. Defect detection of photovoltaic modules based on improved VarifocalNet. *Scientific Reports*, 2024, vol. 14, article no. 15170. DOI: 10.1038/s41598-024-66234-3.

19. Dhimish, M., & Badran, G. Photovoltaic Hot-Spots Fault Detection Algorithm using Fuzzy Systems. *IEEE Transactions on Device and Materials Reliability*, 2019, vol. 19, no. 4, pp. 671-679. DOI: 10.1109/TDMR.2019.2944793.

20. Park, Y. Optimal and robust design of brain-state-in-a-box neural associative memories. *Neural Networks*, 2010, vol. 23, no. 2, pp. 210–218. DOI: 10.1016/j.neunet.2009.10.008.

21. Prabhakaran, S., Uthra, R. A., & Preetharoselyn, J. Deep Learning-Based Model for Defect Detection and Localization on Photovoltaic Panels. *Computer Systems Science & Engineering*, 2023, vol. 44, no. 3, pp. 2683-2700. DOI: 10.32604/csse.2023.028898.

22. Sevrani, F., & Abe, K. On the Synthesis of Brain-State-in-a-Box Neural Models with Application to Associative Memory. *Neural Computation*, 2000, vol. 12, no. 2, pp. 451–472. DOI: 10.1162/089976600300015871.

23. Bodyanskiy, Y. V., & Teslenko, N. A. Adaptive learning of fuzzy BSB and GBSB neural models. *Cybernetics and Systems Analysis*, 2006, vol. 42, pp. 786–794. DOI: 10.1007/s10559-006-0119-y.

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ІНТЕЛЕКТУАЛЬНА СИСТЕМА ВИЯВЛЕННЯ ТА КЛАСИФІКАЦІЇ ДЕФЕКТІВ СОНЯЧНИХ ПАНЕЛЕЙ У РЕАЛЬНОМУ ЧАСІ

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Предметом дослідження у статті є процес виявлення та класифікації дефектів сонячних панелей у режимі реального часу за допомогою безпілотних літальних апаратів (БПЛА) та технологій штучного інтелекту. **Метою** роботи є розробка інтелектуальної системи моніторингу, яка яка поєднує методологію активного моніторингу з моделлю на основі нечіткої BSB для виявлення та класифікації дефектів сонячних панелей у режимі реального часу. Це дозволить своєчасно виявляти дефекти та зменшити витрати на ремонт або заміну сонячних панелей. **Завдання**, що потребують вирішення: розробити метод активного моніторингу стану панелей на основі лазерного сканування; інтегрувати алгоритми обробки даних та класифікації дефектів у режимі реального часу; дослідити застосування моделі Fuzzy BSB (Braine-State-in-the-Box) для підвищення стабільності класифікації в умовах шуму та неповних даних. Використані **методи**: активне лазерне сканування з безпілотних літальних апаратів, алгоритми нечіткої нейронної мережі, модель асоціативної пам'яті Fuzzy BSB, а також методи аналізу зображень та векторів ознак. Були отримані наступні **результати**. Запропоновано методологію виявлення дефектів на етапі транспортування та під час експлуатації сонячних панелей. Запропоновано модель Fuzzy BSB для класифікації виявлених дефектів, яка здатна забезпечити точність близько 80% навіть в умовах значного шуму та перекриття класів. Встановлено, що система ефективно розрізняє основні типи дефектів, зокрема тріщини, забруднення, затінення та механічні пошкодження, демонструючи конкурентні переваги порівняно з традиційними пасивними методами. **Висновки.** Наукова новизна отриманих в процесі дослідження результатів полягає в наступному: 1) адаптація комбінації асоціативної пам'яті та нечіткої логіки в моделі Fuzzy BSB до класифікації дефектів сонячних панелей, що дозволяє підвищити достовірність цієї класифікації в умовах неповних або зашумлених даних; 2) запропоновано концепцію інтеграції активного лазерного сканування з інтелектуальними алгоритмами аналізу, що відкриває перспективи для створення гнучких та адаптивних систем моніторингу стану сонячних електростанцій.

Ключові слова: сонячні панелі; дефекти; лазерне сканування; безпілотні літальні апарати; нейронні мережі; інтелектуальна система; Fuzzy BSB.

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