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Fuzzy Brain-State-in-a-Box neural network for intelligent classification of solar panel defects

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ABSTRACT

The article considers the problem of intelligent classification of solar panel defects in remote monitoring systems based on unmanned aerial vehicles. The relevance of the study is due to the need to increase the accuracy of automated diagnostics of photovoltaic systems in conditions of incomplete data, the presence of noise components and partial overlap of features of different types of defects. The use of traditional computer vision methods and deep neural networks for unmanned aerial vehicle monitoring tasks is often accompanied by significant computational complexity, the need for a large amount of training data and the complexity of implementation on low-power edge-AI platforms. In this regard, the development of compact intelligent classification models capable of operating in conditions of limited computing resources is relevant. **The work aims** to develop a fuzzy neural model Fuzzy Brain-State-in-a-Box, for intelligent classification of solar panel defects in a compact feature space. The proposed approach combines the mechanisms of Brain-State-in-a-Box associative memory, fuzzy inference and prototypical class representation within a single hybrid architecture. The research **methodology** is based on the formation of a five-dimensional feature space after preprocessing and dimensionality reduction of experimental data. To increase the stability of the classification, a temperature-controlled fuzzy membership evaluation mechanism was used, which provides adaptive regulation of the level of fuzziness of the classification solution. As part of the study, a software implementation of the Fuzzy Brain-State-in-a-Box model was performed and experimental studies were conducted on a dataset of one thousand samples. The results confirmed the effectiveness of the proposed approach and provided a classification accuracy of ninety-one percent, a macro-F1 measure at the level of eighty-nine hundredths and Cohen's Kappa at the level of eighty-six hundredths. The analysis showed that the use of fuzzy degrees of membership and prototypical representation of classes allows for increasing the model's resistance to noise and partial overlap of features. **The practical significance** of the work lies in the possibility of using the developed Fuzzy Brain-State-in-a-Box model in systems for monitoring and diagnosing defects of solar panels based on unmanned aerial vehicles and edge-AI platforms, where low computational complexity, compactness of the algorithm and the ability to work in real time are important.

Keywords: Solar panels; defect classification; Fuzzy Brain-State-in-a-Box; fuzzy neural networks; unmanned aerial vehicle monitoring; associative memory; hypercube; hypersphere

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INTRODUCTION

The rapid transition of the global economy to low-carbon models determines the strategic importance of renewable energy sources (RES), among which solar energy occupies a leading position in terms of growth rates and availability [1], [7], [8]. Photovoltaic (PV) panels are the foundation of modern decentralized energy, allowing territorial communities and industrial facilities to achieve energy independence and reduce environmental burden. However, the efficiency of such systems critically depends on the technical condition of each individual photovoltaic cell throughout the entire life cycle of operation.

Long-term operation of solar panels in an open environment inevitably leads to the appearance of various defects: from surface contamination and shading to structural damage, such as microcracks, contact corrosion and thermal anomalies (“hot spots”). Even seemingly insignificant defects initiate a chain reaction: they cause local overheating, which accelerates the degradation of semiconductor materials, significantly reduces the efficiency of the system and can lead to complete failure of the panel or even fire [2], [11].

Detecting these problems at an early stage is a challenging task. Traditional ground inspection methods using handheld thermal imagers are too time-consuming, labor-intensive, and inefficient for large-scale solar parks [19], [20]. In this context, the use of unmanned aerial vehicles (UAVs) equipped with multispectral and thermal cameras becomes critical [3], [24]. UAVs allow for rapid monitoring of large areas, obtaining highly accurate data on the set was generated under conditions of natural lighting and stable insolation, typical of the standard operating mode of photovoltaic systems. The obtained data, after pre-processing and dimensionality reduction, were used to construct a feature space and further classify defects using the FBSB method. However, obtaining data using UAVs is only the first stage. The main challenge remains the intelligent processing of the obtained images in real time, especially in conditions of noisy data and variability of weather conditions. This research is devoted to the development of advanced methods of defect classification based on fuzzy neural networks of associative memory, which allows automating the diagnostic process, ensuring high recognition accuracy and minimizing the influence of the human factor, which is key for the stable functioning of modern “green” energy [16]. The practical significance of the work lies in the possibility of using the developed FBSB model in systems for monitoring and diagnosing defects of solar panels based on unmanned aerial vehicles and edge-AI platforms, where low computational complexity, compactness of the algorithm and the ability to work in real time are important.

RELATED WORKS

The current state of scientific research in the field of monitoring renewable energy facilities (RES) is characterized by the transition from manual inspection to fully autonomous systems based on unmanned aerial vehicles (UAVs) and artificial intelligence [18]. An analysis of publications in recent years shows that the leading direction is the creation of intelligent energy ecosystems of territorial communities. Researchers in [5], [6], [23], [26] emphasize the advantages of using fuzzy logic and reinforcement learning for adaptive control of such systems, but note the disadvantage of high computational complexity for implementation on low-power embedded platforms and edge-AI devices.

A separate body of literature is devoted to Edge AI – on-board data processing directly on UAVs. The authors of [8[, [9], [25] demonstrate high accuracy in hot spot detection on panels using drones, enabling real-time defect detection. One of the most common approaches for automated defect detection in UAV monitoring systems is the YOLO family of architectures, which provides high image processing speed and effective localization of defective areas. At the same time, such models require significant computational resources, a large amount of training data, and a complex retraining procedure, which limits their use in compact edge-AI systems. The condition of infrastructure, and detecting temperature anomalies those are invisible to the human eye.

The study involved the use of a UAV platform for remote monitoring of solar panels using thermal imaging and RGB sensors. The experimental data set was generated under conditions of natural lighting and stable insolation, typical of the standard operating mode of photovoltaic systems. The obtained data, after pre-processing and dimensionality reduction, were used to construct a feature space and further classify defects using the FBSB method. However, obtaining data using UAVs is only the first stage. The main challenge remains the intelligent processing of the obtained images in real time, especially in conditions of noisy data and variability of weather conditions. This research is devoted to the development of advanced methods of defect classification based on fuzzy neural networks of associative memory, which allows automating the diagnostic process, ensuring high recognition accuracy and minimizing the influence of the human factor, which is key for the stable functioning of modern “green” energy [16]. The practical significance of the work lies in the possibility of using the developed FBSB model in systems for monitoring and diagnosing defects of solar panels based on unmanned aerial vehicles and edge-AI platforms, where low computational complexity, compactness of the algorithm and the ability to work in real time are important.

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Unlike the classic post-processing scheme of data on the ground workstation, on-board processing allows for primary defect classification directly during the UAV flight. This approach reduces the amount of transmitted data, reduces delays between the monitoring and decision-making stages, and allows for the rapid localization of potentially defective areas of solar panels in real time. This is especially important for large photovoltaic plants, where full post-processing of high-resolution images can require significant time and computational resources.

In the context of sustainable environmental management [10] focuses on multispectral monitoring of vegetation around photovoltaic plants. This allows assessing the impact of energy facilities on the ecosystem, although most existing solutions operate in post-processing mode, which makes it impossible to respond promptly to soil erosion or pollution [15], [22]. Cybersecurity issues in such systems become critical, since standard UAV control protocols (e.g. MAVLink) have vulnerabilities to interception [16], [21]. [17] proose federated learning for secure communication, which increases confidentiality, but complicates the overall system architecture.

Neural network models of the "Brain-State-in-a-Box" (BSB) types are considered as an effective alternative to deep learning for specific associative recognition tasks [13]. Their advantage is the ability to work with imprecise data and small samples. However, the classical BSB model has a disadvantage – it does not always provide separation of closely spaced defect classes.

Based on the analysis, it was found that the key problem is the lack of a comprehensive secure technological chain that would combine operational on-board identification of panel defects with guaranteed data integrity. Therefore, the main task of the research is to develop a method and intelligent information technology based on fuzzy neural networks of associative memory (FBSB) and hardware-accelerated computing [27] for autonomous monitoring and classification of solar panel defects in real time, while ensuring high diagnostic accuracy in conditions of uncertainty.

RESEARCH AIM AND OBJECTIVES

This work aims to develop a methodology for intelligent classification of solar panel defects based on the fuzzy associative neural network Fuzzy Brain-State-in-a-Box (FBSB), which provides high diagnostic accuracy under conditions of incomplete, noisy, and partially overlapping data and can be used to implement UAV-based solar panel monitoring and defect diagnosis systems.

To achieve the set goal, it is necessary to solve the following scientific and practical problems:

– to conduct a critical review of existing methods for classifying defects in photovoltaic panels, to identify the shortcomings of deep learning when working with small samples, and to justify the feasibility of using fuzzy associative memory models;

– develop a modified mathematical model of a Fuzzy BSB that integrates data-driven class prototyping via centroids and a temperature-driven membership function to improve the resolution between close defect classes;

– combine the use of the Fuzzy Brain-State-in-a-Box model with a centroid-oriented representation of classes in a hyperspherical feature space for solar panel defect classification problems;

– design and implement the architecture of the software complex (FBSB pipeline), which includes modules for stratified data preprocessing, automated selection of hyperparameters (temperature scanning), and visualization of results in the form of error matrices;

– to test the developed technology on real data from laser scanning of solar panels, assess its sensitivity to interference, and substantiate the possibility of on-board implementation on UAVs, taking into account the requirements for data integrity in communication channels;

– evaluate the results of model training and testing, proving the ability to identify critical defects.

RESEARCH METHODOLOGY

The classical BSB method described in [13], which is used for data clustering, is not efficient enough for complex tasks or large amounts of data, since its architecture is limited by a specific form of state storage. In addition, the BSB algorithm works better with already familiar patterns, but may not be able to adapt and learn new ones effectively, especially in conditions of data distortion. Classical BSB is mostly suitable for associative memory and pattern recognition tasks, so it is not a universal solution for tasks of processing imprecise data.

To eliminate these shortcomings, it is proposed to use Fuzzy BSB [11], [12], [13], [14] for data processing, which combines the properties of associative memory with fuzzy clustering mechanisms, allowing to restore and classification of data even under conditions of partial loss of information or the presence of noise. Due to the construction based on the hypercube in the classical BSB and the introduction of the formation of fuzzy membership functions, the proposed Fuzzy BSB method has a number of advantages, which are described below.

When using the classical BSB method, all data is placed inside a hypercube $[-1;1]^n$ [12].

The input data is normalized to the range [-1; 1], which allows us to place vectors in the hypercube spaces accordingly:

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

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

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

Let's find the coefficients a and b:

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

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

$$a = 1 - \frac{2x_{max}}{x_{max}-x_{min}} = \frac{x_{max}-x_{min}-2x_{max}}{x_{max}-x_{min}} = \frac{-x_{max}-x_{min}}{x_{max}-x_{min}} = \frac{-(x_{max}+x_{min})}{x_{max}-x_{min}} = \frac{x_{max}+x_{min}}{x_{min}-x_{max}}.$$

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

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

Let $\tilde{x}^k \in R^n$ be the input feature vector at iteration k, where n = 5.

The network state is updated according to the rule:

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

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

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

The BSB fuzzy model takes into account the distance between the current input and the vertices of the hypercube to calculate the membership function [11]:

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

where x_q is the qth vertex of the hypercube.

The temperature parameter is the degree of "rigidity" of the classification decision in the FBSB model. At small values of T, the membership function approaches a rigid choice of the closest prototype, while as T increases; a smoother distribution of membership degrees between classes is formed. Thus, the temperature parameter T controls the level of classification fuzziness and affects the stability of decision-making in the case of partial overlap of classes in the feature space:

$$\mu_q(x) = \frac{\exp\left(-\frac{d(x,c_j)}{T}\right)}{\sum_{j=1}^{C}\exp\left(-\frac{d(x,c_j)}{T}\right)}, \quad (8)$$

where $d(x, c_q)$ is the distance between the input feature vector x and the centroid c_q of the qth class, C is the number of classes, and T is the temperature parameter of the fuzzy output.

The closer x is to the vertex, the greater 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 $W = \sum_{k=1}^{l} \tilde{x}^{(k)}(\tilde{x}^{(k)})^T$.

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

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

where η is the learning rate.

After training, the predicted value ŷ for a new input x is calculated as a weighted sum over the clusters:

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

where y_q is the averaged output value associated with cluster q.

All data are pre-centered and normalized (Z-score):

$$\tilde{x}_i(k) = \frac{x_i(k) - \bar{x}_i}{\sigma_i}\,, \tag{11}$$

where $\bar{x}_i = \frac{1}{N}\sum_{k=1}^{N} x_i(k)$ – the sample mean and $\sigma_i = (\frac{1}{N-1}\sum_{k=1}^{N}(z_i(k) - \bar{x}_i)^2)^{\frac{1}{2}}$ –standard deviation.

Z-normalization is used exclusively as an intermediate step in standardizing features to eliminate the influence of different data scales. After that, the final encoding of the input variables to the interval $[-1;1]$, which meets the requirements of the classical BSB model, was performed.

In most neural networks with activation functions such as sigmoid or hyperbolic tangent, the data are normalized to the interval [-1; 1] in such a way that $-1 \le \hat{x}_i \le 1$, which is achieved by linear scaling

$$\hat{x}_i(k) = 1 - \frac{2(\tilde{x}_{i\max} - \tilde{x}_i(k))}{\tilde{x}_{i\max} - \tilde{x}_{i\min}}\,. \tag{12}$$

All observations $\hat{x}_i(k)$ at $\forall i, k$ are located within [-1; 1] each, that is, geometrically all coordinates vary within the unit hypercube as shown in Fig. 1.

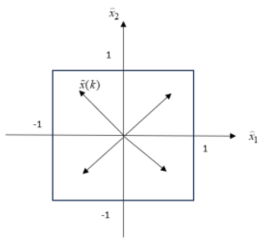

Fig. 1. **Location of normalized variables on a hypercube**
***Source*: prepared by the authors**

For self-learning of SOM-type neural networks (Kohonen map), all data are normalized to a hypersphere with unit radius so that:

$$\hat{x}(k) = \frac{\tilde{x}(k)}{\|\tilde{x}(k)\|_2}\,, \tag{13}$$

where $\|*\|_2$ is Euclidean norm. In this case, all observations are located on the surface of the hypersphere as shown in Fig. 2. This ensures the same length of vectors and simplifies the procedure for finding the nearest neuron by Euclidean distance.

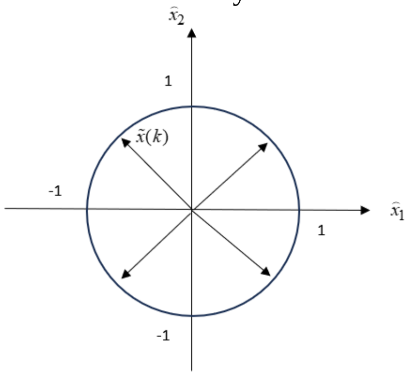

Fig. 2. **Location of normalized variables on a hypersphere**
***Source*: prepared by the authors**

In the proposed FBSB architecture, hyperspherical and hypercubic geometries are used at different stages of the model functioning and perform different functions. Data normalization to a unit hypersphere is used at the stage of forming the feature space and determining the cluster centers, since such a geometry provides stable calculation of Euclidean distances between vectors and allows searching for the nearest class centers by analogy with the SOM mechanism.

It is worth noting that within the framework of the study, the hyperspherical representation is used exclusively for normalizing the feature space and stabilizing the centroid-oriented representation of classes. The classical Kohonen SOM map learning algorithm is not used in the work.

After determining the cluster centers, the resulting centroids are projected into the space of a unit hypercube, within which the dynamics of the BSB network are implemented. Thus, the hypersphere is used for geometric stabilization and the formation of a compact feature space, while the hypercube is used to implement the associative memory mechanism and fuzzy decision-making.

Within the FBSB model, the classification process consists of two consecutive stages. In the first stage, centroids are formed for each class in the normalized feature space. In the second stage, fuzzy

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estimation of the degrees of membership between the input vector and the class centroids is performed using the dynamics of the BSB network and the temperature-controlled fuzzy inference function. This approach provides the integration of associative memory, geometric clustering, and fuzzy decision-making mechanisms within a single hybrid architecture.

The geometric representation of the unit region in the feature space depends on the chosen metric. In particular, in the Euclidean metric L_2 the unit region has the shape of a hypersphere, while in the Chebyshev metric L_∞ it takes the shape of a hypercube:

$$\left|\hat{x}_1\right|+\left|\hat{x}_2\right|=1,\ \sum_{k=1}^{N}\left|\hat{x}_i\right|=1 \text{- Manhattan metric}$$

$$\left|\hat{x}_1\right|^2+\left|\hat{x}_2\right|^2=1,\ \sum_{k=1}^{N}\left|\hat{x}_i\right|^2=1 \text{ – Euclidean metric}$$

$$\left|\hat{x}_1\right|^\infty+\left|\hat{x}_2\right|^\infty=1,\ \sum_{k=1}^{N}\left|\hat{x}_i\right|^\infty=1 \text{ – Chebyshev metric.}$$

Using BSB allows you to find out how many clusters-classes (hypercube), and the actual clustering, with finding the centers, can be done using the Kohonen map on the hypersphere. In this case, the condition must be

$$-1 \le \hat{x}_i(k) \le 1. \tag{14}$$

The BSB fuzzy model effectively combines associative memory and fuzzy logic for detecting and classifying defects in solar panels. It exhibits high noise immunity and the ability to handle cluster intersections, making it suitable for practical use in bioenergy plant diagnostics and optimization tasks.

EXPERIMENTS

The developed software implements a defect classification method based on a Fuzzy BSB with a prototypical representation of classes, which is focused on processing multidimensional feature vectors and making interpreted decisions in the tasks of technical diagnostics of renewable energy facilities and is described in subsection 3.3. The algorithmic principles of the FBSB method are set out in the theoretical part of the dissertation work, while this software provides their practical implementation, taking into account the requirements of numerical stability, reproducibility of results and automated assessment of classification quality.

The input information for the software tool is numerical feature vectors formed based on the pre-processing of thermal UAV images of solar panels and the analysis of temperature anomalies of defective areas. The study analyzed only the features obtained after pre-processing of remote monitoring data of solar panels. Methods of mechanical control, stress measurement or laser scanning were not used in the work. In the framework of the experiments, such vectors are 5-dimensional features obtained after dimensionality reduction (PCA), and the output variable is a discrete index of the defect class.

The input feature space was formed on the basis of pre-processed remote monitoring data of solar panels and contained five informative features obtained after dimensionality reduction by PCA. The formed features characterize the generalized geometric and temperature state of photovoltaic modules and are used as a compact representation of the defective profile of the panel in the feature space. The use of a reduced five-dimensional space allowed reducing the influence of noise and excess correlated parameters on the classification results. The software implementation is focused on working with tabular data in CSV format, which allows it to be easily integrated with other software tools for data preprocessing and analysis.

To ensure reproducibility of the results, all experiments were performed in the Python environment using the same parameters of stratified data distribution, pre-normalization and fuzzy inference procedure. The feature space formation was carried out for all samples according to the same scheme of experimental data pre-processing.

After reading the data, their basic processing is performed, which includes converting the variable types to a numerical format and forming a matrix of features and a vector of class labels. Special attention is paid in the software to normalization, since the FBSB method is lag-oriented, and the degrees of fuzzy membership directly depend on the geometric relationships between the vectors. For this purpose, a two-stage procedure is implemented: first, z-normalization is performed according to the statistics of the training sample, after which the features are linearly scaled to the interval [-1;1]. This approach ensures the consistency of the scales, eliminates the dominance of individual variables, and creates the prerequisites for the correct interpretation of the bipolar feature space.

In the normalized space, the software generates prototypes of classes, which are defined as the centroids of the corresponding training subsets. Each prototype is a generalized representation of the class and at the same time an interpreted object, which allows analyzing the reasons for the decision made through the distances to the prototypes. Unlike the classical implementation of BSB networks with fixed encoding of classes in the vertices of the hypercube, the proposed software uses a data-oriented representation of classes, which ensures that the model matches the real data distribution in the feature space.

The key stage of the software tool is the fuzzy excitation of the FBSB network. For each test vector, the distances to all class prototypes are calculated, after which a vector of degrees of membership is formed using a temperature-controlled exponential function. The temperature parameter T determines the degree of "rigidity" of decision-making: at small values of T, the model behaves like a rigid classifier of the nearest prototype, while with increasing values of T, the influence of distant prototypes increases and the decision becomes more fuzzy. To adapt the model to the structure of the experimental data, a temperature scanning procedure was used in the software implementation. Within this approach, the parameter T was changed in a given range of values, and for each temperature value, the classification accuracy was re-evaluated. This approach allowed to investigate the sensitivity of the model to changes in the level of fuzziness and to select the region of stable operation of the FBSB classifier. The final class is determined according to the principle of maximum degree of membership, which is consistent with the classical scheme of fuzzy inference of the "winner takes all type.

The temperature parameter setting is implemented directly in the software by iterating over values on a given grid and providing feedback to the quality assessment subsystem. For each value T, the test sample is classified and a set of metrics is calculated, after which the optimal value is selected that maximizes the generalized quality indicator. This mechanism allows you to adapt the model to a specific data set without involving expert parameter tuning.

The evaluation subsystem implements an extended set of metrics that allows for a comprehensive proof of the model's correctness. In addition to the overall classification accuracy, Macro-F1, Balanced Accuracy, Cohen's Kappa coefficient of agreement, and ROC-AUC in the "one-vs-rest" setting based on fuzzy membership estimates are calculated. In addition, an error matrix and class-specific Precision, Recall, and F1 measures are generated, which allows for a detailed analysis of the model's behavior for each defect type. All classification metrics were calculated based on the defuzzified original class labels obtained using the maximum degree of membership criterion.

From the data flow perspective, the software tool forms a closed computational pipeline, in which the normalization results are directly used to form prototypes and fuzzy excitation, and the initial solutions are fed into the evaluation and results generation subsystem. The final stage is the automated export of results in the form of tables and graphics. Such architecture ensures the transparency of algorithmic logic, the interpretability of decisions made, and the reproducibility of experimental results, which is fundamentally important for the tasks of technical diagnostics and monitoring the condition of complex engineering systems.

The fragment presented in Fig. 3 reflects the structural diagram of the software tool for implementing the FBSB method, in which each block corresponds to a separate stage of software data processing and is logically connected with the subsequent stages of forming a classification solution.

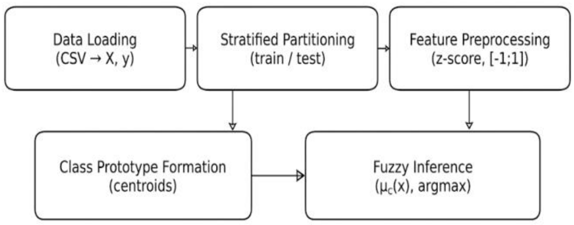

Fig. 3. **Structure of the FBSB software package with data separation into training and test subsamples**
***Source*: prepared by the authors**

The software tool starts with the data loading block (CSV → X, y), which is responsible for importing the experimental sample from a CSV file and converting it into an internal representation in the form of a feature matrix X_i and a class label vector y. The experimental sample contained 1000 samples, represented by five informative features, formed after the stage of dimensionality reduction and data preprocessing. To ensure the correctness of the assessment of the classification quality, a stratified division of the data into training and test subsamples was used, while preserving the initial class ratio. This approach allowed to reduce the impact of class imbalance and ensured the representativeness of the experimental study.

At this stage, the software tool checks the correctness of the data structure, the number of features and classes, and also ensures the consistency of data types for further numerical calculations. It is this block that forms a single-entry

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point for integrating the FBSB implementation with other software components of the data analysis system.

The pseudocode presented in Fig. 4 formalizes the initial stage of the functioning of the FBSB implementation software, which is responsible for reading experimental data from a CSV file and forming an internal representation in the form of a feature matrix X_i and a class vector y. At this stage, the structural integrity of the data is ensured, the unambiguous separation of the target variable from the feature description and the preparation of information for subsequent procedures of stratified distribution, normalization and fuzzy inference.

```
Input data:
    csv_file        - path to CSV file with data
    target_column   - name of the column corresponding to the class

Output data:
    X               - feature matrix of dimension N × d
    y               - vector of class labels of length N

Start
    1. Open CSV file csv_file
    2. Read the first line of the file as a list of column names
    3. Check for the existence of the column target_column
       If target_column is not found, then
           Generate an error message and terminate execution
       End If

    4. Initialize empty lists X_list, y_list

    5. For each subsequent line of the CSV file do
           5.1. Read the values of all columns
           5.2. Extract the class value y_i from the target_column
           5.3. Delete the target_column from the current line
           5.4. Transform the remaining values into a numerical x_i
           5.5. Add x_i to X_list
           5.6. Add y_i to y_list
       End For

    6. Transform X_list into a numerical matrix X of dimension N × d
    7. Transform y_list into a vector of labels y of length N

    8. Return X, y
End
```

Fig. 4. **Pseudocode of the data loading module**

***Source*: prepared by the authors**

Next, the information flow passes to the data distribution block (train / test), which implements the experimental protocol of the software tool. Here, the input sample is divided into training and test subsets while preserving the initial class distribution. This approach is fundamentally important for the implementation of FBSB, since class prototypes are formed exclusively from the training data, and the classification quality is assessed on an independent test subsample. Stratified distribution ensures the reproducibility of the results and the correctness of statistical estimates. The pseudocode of this block is shown in Fig. 5.

Two parallel data streams are formed from the stratified distribution block. The first stream is transmitted to the class prototype (centroid) formation block. Within this block, the software implements the key idea of FBSB – data-oriented representation of classes (Fig. 6). Formation of class prototypes in the FBSB software is carried out by calculating centroids for each class in the normalized feature space. For each class, all training samples belonging to it are selected, after which the

```
Input:
    X            - feature matrix of dimension N x d
    y            - vector of class labels of length N
    test_ratio   - fraction of the test sample (0 < test_ratio < 1)
    seed         - seed value for the random number generator

Output:
    X_train, y_train - training sample
    X_test,  y_test  - test sample

Begin
    1. Initialize the random number generator with the value seed
    2. Determine the set of unique classes C = unique(y)
    3. Initialize empty lists:
           train_indices, test_indices

    4. For each class c ∈ C do
           4.1. Determine the indices Ic = { i | y[i] = c }
           4.2. Shuffle the indices Ic in random order
           4.3. Calculate the number of test samples:
                    n_test_c = round(|Ic| × test_ratio)
           4.4. Add the first n_test_c indices of Ic to test_indices
           4.5. Add the remaining indices of Ic to train_indices
       End For

    5. Shuffle train_indices and test_indices
    6. Form the training sample:
           X_train = X[train_indices]
           y_train = y[train_indices]
    7. Form the test sample:
           X_test = X[test_indices]
           y_test = y[test_indices]

    8. Return X_train, y_train, X_test, y_test
End
```

Fig. 5. **Pseudocode for implementing the data distribution block**

***Source*: prepared by the authors**

average feature vector is calculated, which is considered a compact representation of the class. The formed centroids are used as reference states of the associative memory of the BSB network. In the process of fuzzy inference, the input vector is iteratively compared with the centroids of the classes in the hypercube space, and the network dynamics ensure convergence to the closest prototype. Thus, the centroids play the role of stable attractor-state structures within the BSB model. The resulting prototypes are interpreted as parameters of the model, since they allow analyzing the classifier solution through the distances between the input vector and the class centroids. Subsequently, these prototypes are used in the fuzzy inference block to form degrees of membership and determine the final class.

The second stream from the stratified distribution block enters the feature reprocessing block (z-score, [-1;1]), where the data normalization procedure is implemented. In the software, this reprocessing includes z-normalization and further scaling of feature values to the interval [-1;1], which is consistent with the bipolar nature of the FBSB representation. The reprocessed features are used both for prototype formation and for further fuzzy inference, which ensures correct comparison of distances in the feature space. The use of a compact feature space allows the FBSB model to effectively separate defect classes even in the presence of partial feature overlap and noise components in the input data. The generalized feature representation also reduces the sensitivity of the model to variations in shooting and lighting conditions.

```
Input:
    Xn_train    – normalized training feature matrix of size Ntr × d (values within [−1;1])
    y_train     – vector of class labels of length Ntr

Output:
    classes     – ondered list-ondered list of unique classes
    P           – matrix of prototypes (centroids) of dismensions C × d, where
                  the row P[c] is the prototype for class classes[c]

Begin
    1. Determine the set of unique classes:
            classes = unique(y_train)
       (if necessary, soprimate classes in ascending order)

    2. Initialize an empty matrix P of size C × d

    3. For each class c from classes do
            3.1. Determine the indices Ic = { i | y_train[i] = c }
            3.2. Select the class feature subset:
                      Xc = Xn_train[Ic, :]
            3.3. Calculate the prototype as the mean vector:
                      p_c[j] = mean(Xc[:, j])   for j = 1..d
            3.4. Write p_c into the corresponding row of matrix P
       End For

    4. Return classes , P
End
```

Fig. 6. **Pseudocode for centroid formation**
***Source*: prepared by the authors**

The results of the prototype generation and feature reprocessing blocks converge in the fuzzy inference block ($\mu_c(x)$ argmax), which is the central computational core of the FBSB implementation software. The proposed system does not perform the functions of automatic control or generation of control signals, but implements intelligent classification of the technical condition of solar panels based on fuzzy feature space analysis. The fuzzy inference block implements the central decision-making mechanism in the FBSB software. For each normalized test vector, the distances to the class prototypes are calculated, after which a vector of fuzzy degrees of membership $\mu_c(x)$ is formed through exponential decay depending on the distance. The fuzzy decision-making mechanism is integrated with the BSB dynamics by using membership degrees as weights when assessing the proximity to the class centers. As a result, the neural network dynamics provides stabilization of the system state, and the fuzzy inference allows for soft separation of classes in the case of their partial overlap. The temperature parameter T controls the distribution of memberships. To ensure numerical stability, softmax stabilization is applied by subtracting the maximum value z_{max}, and the eps parameter is also used to avoid division by zero. The output $\hat{y} = argmax_q \mu_q(x)$ is the predicted class and a matrix of fuzzy memberships, which can be used for additional analysis of the model quality. The defuzzification procedure in the FBSB model is implemented according to the principle of maximum degree of membership (argmax). The object belongs to the class for which the membership function acquires the greatest value. It is the hard class labels obtained after defuzzification that are used to construct the error matrix and calculate the accuracy, macro-F1, and other metrics.

Experimental research of the software implementation of the FBSB method was carried out with the aim of comprehensively assessing its classification properties, robustness to hyperparameter variations, and correctness of the internal decision-making dynamics. For this purpose, a dataset of solar panel defects in the form of numerical feature vectors was used, and the results were analyzed on an independent test sample.

The first element of the experimental analysis is the classification error matrix, which is presented in Fig. 7. This graph displays the distribution of true and predicted classes and allows us to assess in detail the nature of the software errors. The classes used in the confusion matrix correspond to the following defect categories: class 0 (Normal) – operating condition without detected defects or thermal anomalies, class 1 (Hot Spot) – representing local overheating regions of the photovoltaic module, class 2 (Crack) – corresponding to cracks or microcracks in the solar panel structure, class 3 (Delamination) – indicating separation of structural layers within the photovoltaic module, and class 4 (Corrosion) – representing corrosion damage of conductive elements or electrical contacts of the solar panel. The construction of the error matrix was performed after the defuzzification procedure, in which each test sample was assigned one hard class according to the maximum value of the membership function. The diagonal elements of the matrix

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correspond to correctly classified samples and have dominant values, which indicates a high overall accuracy of the model. Small off-diagonal elements indicate a limited number of mutual errors between individual classes of defects, which, as a rule, are close in their characteristics. Analysis of the error matrix confirms that FBSB does not demonstrate a systematic bias towards a separate class, and the errors are local in nature.

For a generalized quantitative assessment of the classification quality, a bar chart of the main metrics was constructed, shown in Fig. 8. This graph presents the values of Accuracy, Macro-F1, Balanced Accuracy, and Cohen's Kappa coefficient.

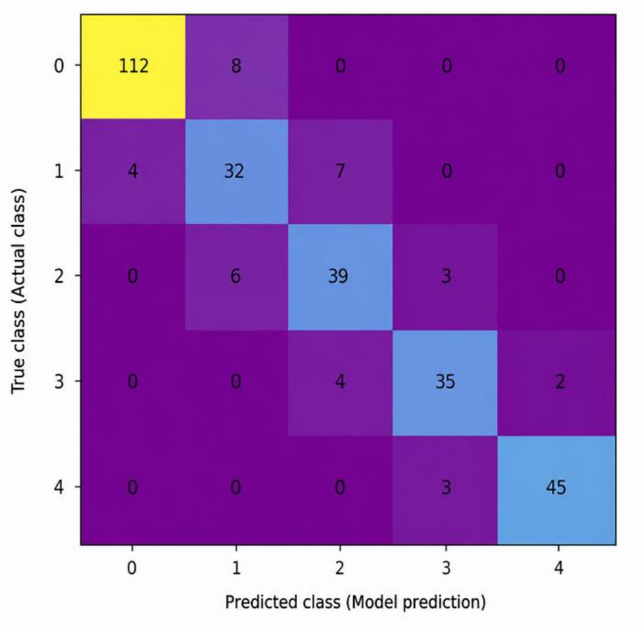

Fig. 7. **Error matrix of solar panel defect classification using FBSB: 0 – Normal; 1 – Hot Spot; 2 – Crack; 3 – Delamination; 4 – Corrosion**

***Source*: prepared by the authors**

High values of all the above indicators confirm the ability of the FBSB software tool to provide not only high overall accuracy, but also balanced recognition quality for all classes, which is especially important in technical diagnostics tasks with a potentially uneven distribution of defects. The value of the Kappa coefficient, significantly different from zero, additionally indicates the consistency of the classification results with the true labels and the absence of random nature of decision-making.

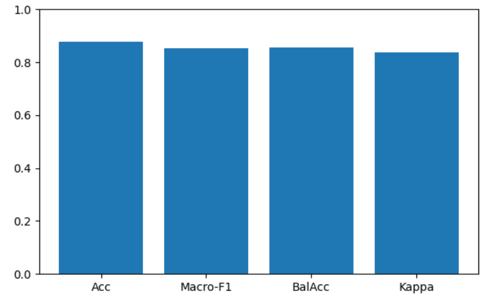

Fig. 8. **Values of the main classification quality metrics for the FBSB software tool**

***Source*: prepared by the authors**

A separate group of experimental results is the analysis of the influence of the temperature parameter T on the quality of classification. The corresponding temperature scan curve is shown in Figure 9. Analysis of the graph shows that in the entire studied range of temperature values $T \in [0.005; 0.08]$. There is no significant decrease in classification accuracy. This is explained by the sufficient separation of class centroids in the feature space, as a result of which a change in the temperature parameter mainly affects the shape of the distribution of fuzzy degrees of membership, and not the final solution of argmax-classification. The curve is almost horizontal without sharp fluctuations or pronounced local maxima. This indicates that the temperature parameter in the FBSB model acts as a regulator of classification fuzziness, and not a critical optimization parameter. The absence of sharp changes in accuracy when changing it confirms the stability of the integration of the fuzzy mechanism into the structure of the BSB network.

This behavior is indicative of the robustness of the model: the fuzzy inference mechanism, built on the exponential transformation of distances to class prototypes, forms a similar distribution of degrees of membership even when the temperature changes. This means that the dominant prototypes for most samples are preserved, and the classifier's decision is not sensitive to small variations in the hyperparameter.

The absence of a sharp maximum or degradation of accuracy with increasing temperature also indicates that the classes are sufficiently well separated in the feature space, and the class prototypes are formed correctly. In such a situation, the temperature parameter plays the role of a stabilizing coefficient rather than a critical setting, which is a positive property of the software tool from the point of view of practical use.

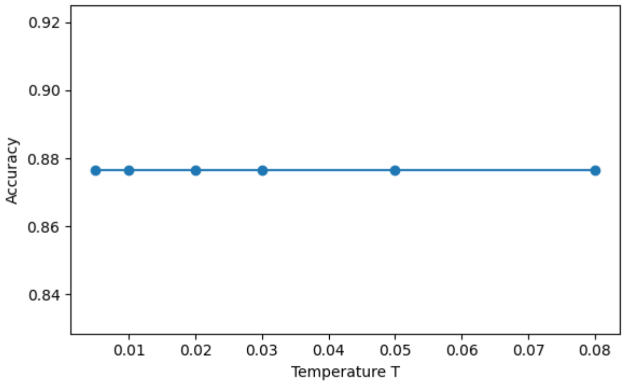

Fig. 9. **Dependence of FBSB classification accuracy on temperature parameter *T***

***Source*: prepared by the authors**

The combined analysis of the presented graphical results allows us to conclude that the FBSB implementation software provides stable and interpretable work in the multi-class defect diagnosis problem.

RESULTS AND DISCUSSIONS

A significant advantage of the proposed Fuzzy BSB method is the ability to train on small samples.

It should be noted that the effectiveness of the proposed FBSB method depends on the quality of the formed feature space and the stability of remote monitoring conditions. The main factors that can affect the classification results are noise components of the input data, partial overlap of defect classes and variations in lighting and isolation conditions during UAV monitoring. At the same time, the use of fuzzy degrees of membership and prototypical representation of classes allows for increasing the model's resistance to such influences and ensuring stable classification of the technical condition of solar panels.

Since the FBSB model operates in a five-dimensional feature space and does not contain a large number of training parameters, the amount of memory for storing centroids and weights is insignificant compared to CNN models. In the software implementation, the average inference time for one feature vector was less than 10 ms on an Intel Core i5 processor, which confirms the possibility of using the algorithm in edge-AI systems and on UAV computing modules.

An additional advantage of FBSB is the absence of the need to perform multi-layer convolution operations, which allows reducing power consumption and computational load during UAV platform operation.

To evaluate the effectiveness of the proposed approach, a comparative analysis was conducted with classical machine learning methods and modern computer vision architectures used for solar panel defect detection and classification tasks. The basic methods considered were the support vector machine (SVM), Random Forest, and the YOLO model, which is widely used in UAV monitoring systems for automated defect detection in thermal and RGB images [28], [29].

The analysis showed that the YOLO model provides high accuracy of defect localization when working with large image arrays, but is characterized by significant computational complexity and requires a large amount of training data. Unlike YOLO, the proposed FBSB method works in a compact space of informative features and does not require multilayer convolutional calculations, which significantly simplifies the implementation of the algorithm in conditions of limited hardware resources (Table 1). Unlike deep CNN architectures, the proposed FBSB model uses a compact feature space and performs classification based on calculating the distances between the input vector and the centroids of the classes. This allows to significantly reduce the computational complexity of the algorithm and the amount of required memory. The main computational costs of the model are associated with normalization operations, calculating Euclidean distances and forming fuzzy degrees of membership, which do not require a large number of parameters or multilayer convolutional operations. In addition, the use of fuzzy membership degrees provides better robustness to partial class overlap and noise components in the feature space.

Table 1. **Comparison of modern classification methods with Fuzzy BSB**

Method	Accuracy	Macro-F1	Features
SVM	0.84	0.82	Sensitivity to class overlap
Random Forest	0.87	0.85	Dependence on the sample structure
YOLO	0.93	0.91	High computational complexity
FBSB	0.91	0.89	High interpretability and noise immunity

***Source*: prepared by the authors**

It should be noted that modern lightweight deep learning architectures, in particular YOLO-based networks, MobileNet-based approaches and Vision Transformer architectures, can in many cases provide higher classification accuracy in the presence of large training samples and significant computational resources. In this work, the main focus is not on achieving state-of-the-art accuracy, but on building a compact and interpretable FBSB approach for edge-AI implementation in conditions of limited hardware resources and small data samples.

The results obtained confirm that the FBSB method is inferior to YOLO in terms of maximum classification accuracy, but provides significantly lower computational complexity, better interpretability, and stability of operation with a limited amount of data, which is important for the implementation of intelligent UAV monitoring systems in real time.

Thus, normalization to a hypercube is convenient for classification tasks where feature boundaries are important, and normalization to a hypersphere is convenient for clustering and visualization where the direction of the vector is of primary importance, not its magnitude.

By combining the two approaches in a BSB–SOM type system, it is possible to achieve sufficiently high accuracy with a limited amount of data, providing a balance between stability (hypersphere) and resolution (hypercube).

Thus, an improved method for classifying solar panel defects based on fuzzy BSB was proposed, which allowed obtaining a training accuracy of 89% and a testing accuracy of 91 %, and also provided the ability to work with a limited set of data from 1000 samples. The small difference between the training and testing accuracy indicates the stability of the proposed model and the absence of critical overtraining. Additional regularization is provided by the use of fuzzy degrees of membership and prototypical representation of classes in the feature space. Stratified sample division ensured the correct representation of classes in the training and testing subsets, which allowed reducing the impact of data imbalance on the classification results. In the proposed FBSB approach, fuzzy membership estimation and centroid-based class representation provide an additional regularization effect that reduces overfitting to individual noisy training samples. The slight excess of testing accuracy over training accuracy is explained by the combination of the effects of stratified random sample division, limited experimental data, and the regularization properties of the FBSB model. The use of fuzzy membership degrees and centroid-oriented class representation reduces overfitting to individual noisy training samples and provides more stable generalization of the model to an independent test sample. This behavior confirms the robustness of the proposed method and indicates a stable generalization ability under conditions of limited and partially overlapping data.

CONCLUSIONS

As a result of the research, an intelligent information technology for diagnosing defects in solar panels was developed and validated, based on fuzzy associative memory neural networks (FBSB) and remote monitoring data from UAVs. The developed system performs the functions of intelligent classification and defect diagnostics, rather than the functions of automatic control of an energy facility. The use of the modified FBSB model allowed for effective classification of the technical condition of photovoltaic cells in conditions of limited and noisy sampling, achieving a testing accuracy of 91 % when working with an experimental dataset of 1000 samples. A mathematical combination of mechanisms by analogy with the Kohonen map on a unit hypersphere with BSB network dynamics within a hypercube provided a stable location of cluster centers and improved resolution between close defect classes. The formal division of functions between the hyperspherical stage of cluster center formation and the hypercubic dynamics of BSB allowed the integration of geometric clustering, associative memory, and fuzzy inference mechanisms within single hybrid FBSB architecture.

A comparative analysis with the SVM, Random Forest, and YOLO methods confirmed that the proposed FBSB approach provides competitive classification accuracy with significantly lower computational complexity and higher interpretability of results, which is important for the implementation of monitoring systems based on UAVs and edge-AI platforms.

The computational complexity analysis showed that the FBSB model does not require significant hardware resources, is characterized by a small amount of memory and low inference complexity, which creates the prerequisites for its use in edge-AI systems and on-board computing modules of UAVs.

The low sensitivity of the model to changes in the temperature parameter has been experimentally proven, which indicates the high stability of the algorithm and the correctness of the generated class prototypes. The introduction of the temperature parameter into the structure of fuzzy inference made it possible to adaptively control the degree of distribution of membership between classes and ensure stable operation of the classifier in conditions of partial overlap of features. The proposed software package, implemented as a closed computational pipeline from data preprocessing to fuzzy inference, creates the prerequisites for on-board implementation of the method on mobile platforms, which will allow automating the monitoring of renewable energy facilities in real time and significantly increasing the efficiency of detecting critical infrastructure damage.

The authors used Grammarly to check the grammar and spelling. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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Нечітка нейронна мережа Fuzzy Brain-State-in-a-Box для інтелектуальної класифікації дефектів сонячних панелей

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АНОТАЦІЯ

У статті розглянуто задачу інтелектуальної класифікації дефектів сонячних панелей у системах дистанційного моніторингу на базі безпілотних літальних апаратів. Актуальність дослідження зумовлена необхідністю підвищення точності автоматизованої діагностики фотоелектричних систем в умовах неповноти даних, наявності шумових компонент та часткового перекриття ознак різних типів дефектів. Використання традиційних методів комп’ютерного зору та глибоких нейронних мереж для задач безпілотний літальний апарат UAV-моніторингу часто супроводжується значною обчислювальною складністю, потребою у великому обсязі навчальних даних та складністю реалізації на малопотужних edge-AI платформах. У зв’язку з цим актуальною є розробка компактних інтелектуальних моделей класифікації, здатних працювати в умовах обмежених обчислювальних ресурсів. **Метою роботи є** розроблення нечіткої нейронної моделі Fuzzy Brain-State-in-a-Box для інтелектуальної класифікації дефектів сонячних панелей у компактному просторі ознак. Запропонований підхід поєднує механізми асоціативної пам’яті Brain-State-in-a-Box, нечіткого виводу та прототипного представлення класів у межах єдиної гібридної архітектури. **Методологія дослідження** базується на формуванні п’ятивимірного простору ознак після попередньої обробки та редукції розмірності експериментальних даних. Для підвищення стійкості класифікації використано температурно-керований механізм нечіткого оцінювання належності, який забезпечує адаптивне регулювання рівня нечіткості класифікаційного рішення. У межах дослідження виконано програмну реалізацію моделі Fuzzy Brain-State-in-a-Box та проведено експериментальні дослідження на наборі даних обсягом одна тисяча зразків. Отримані результати підтвердили ефективність запропонованого підходу та забезпечили точність класифікації дев’яносто один відсоток, macro-F1 міру на рівні вісімдесят дев’ять сотих та Cohen’s Kappa на рівні вісімдесят шість сотих. Проведений аналіз показав, що використання нечітких ступенів належності та прототипного представлення класів дозволяє підвищити стійкість моделі до шуму та часткового перекриття ознак. **Практичне значення роботи** полягає у можливості використання розробленої моделі Fuzzy Brain-State-in-a-Box у системах моніторингу та діагностики дефектів сонячних панелей на базі безпілотних літальних апаратів та edge-AI платформ, де важливими є низька обчислювальна складність, компактність алгоритму та можливість роботи в режимі реального часу.

Ключові слова: сонячні панелі; класифікація дефектів; Fuzzy Brain-State-in-a-Box; нечіткі нейронні мережі; безпілотний літальний апарат UAV-моніторинг; асоціативна пам’ять; гіперкуб; гіперсфера

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