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RESEARCH ARTICLE

Neurovisual recognition of signal radio images

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Abstract
Objectives. The study set out to solve the problem of radiovision classification of objects based on identified features by developing a combined neurovision algorithm for real-time recognition of signal radio images of objects using machine learning (ML) technologies and a fully connected neural network with data augmentation, as well as to improve the probability of correct classification in neurovision signal processing.
Methods. In the study, several methods were used: electrodynamic modeling, machine learning (linear regression, classification, and Random Forest), and deep learning (fully connected neural networks). The bootstrap aggregating (bagging) technique was also employed. An assessment of object classification accuracy metrics and statistical criteria for the reproducibility of radio images was carried out.
Results. A combined neurovision object recognition method was developed that demonstrated a probability of correct classification of at least 0.97 for any of the objects transmitted for training with specified form factors when using augmented data. Data augmentation was shown to increase the neural network's probability of correct classification by 0.04. The obtained results confirm the adequacy of neural network approaches compared to classical ML methods for neurovision object recognition, particularly when dealing with a limited base dataset of objects for neural network training. The proposed method was tested for basic classification of spherical and cubic object models in the centimeter radio frequency range.
Conclusions. Neural networks with data augmentation demonstrate a probability of correct classification exceeding 0.97 for neurovision recognition of radio images as compared to neural networks without data augmentation (0.04 lower) and traditional ML methods (0.13 lower). Although ML methods are inferior to neural networks in radio image reproducibility, they remain indispensable in cases where computational resources are limited. For real-world applications, database expansion through field experiments and the implementation of hybrid neural network architectures are required.

Keywords: neuroimaging method, signal radio image, neural network, machine learning, signature classification, linear regression, random forest, electrodynamic modeling

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НАУЧНАЯ СТАТЬЯ

Нейровизионное распознавание сигнальных радиоизображений

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Резюме
Цели. Целями работы являются: создание комбинированного нейровизионного алгоритма распознавания сигнальных радиоизображений объектов в режиме реального времени с использованием технологий машинного обучения и нейронной сети с полносвязной архитектурой и аугментацией данных; повышение вероятности правильной классификации при нейровизионной обработке сигналов.
Методы. В работе применены методы электродинамического моделирования, машинного обучения (линейная регрессия, классификация, случайный лес) и глубокого обучения (полносвязные нейронные сети). Применена техника бэггинга. Проведена оценка показателей точности классификации объектов и статистических критериев воспроизводимости радиоизображений.
Результаты. Разработан комбинированный нейровизионный метод распознавания объектов, показавший вероятность правильной классификации любого из переданных к обучению объектов с заданными форм-факторами не менее 0.97 при использовании аугментированных данных. Показано, что аугментация данных повышает вероятность правильной классификации нейронной сетью на 0.04. Полученные результаты подтвердили адекватность нейросетевых методов для задач нейровизионного распознавания объектов по сравнению с методами машинного обучения, прежде всего, при ограниченной базовой выборке объектов для обучения нейронной сети. Предложенный метод исследован для базисной классификации сферических и кубических моделей объектов в сантиметровом радиочастотном диапазоне частот.
Выводы. Нейронные сети с аугментацией данных демонстрируют вероятность правильной классификации свыше 0.97 в задачах нейровизионного распознавания радиоизображений в сравнении с нейронными сетями без аугментации данных (ниже на 0.04) и методами машинного обучения (ниже на 0.13). Методы машинного обучения уступают нейросетям в воспроизводимости радиоизображений, однако являются незаменимыми при ограниченных ресурсах вычислительной мощности. Для применения в реальных условиях требуются расширение базы данных за счет натурных экспериментов и применение гибридных архитектур нейронных сетей.

Ключевые слова: нейровизионный метод, сигнальное радиоизображение, нейронная сеть, машинное обучение, классификация радиоизображений, линейная регрессия, метод случайного леса, электродинамическое моделирование

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Авторы заявляют об отсутствии конфликта интересов.

INTRODUCTION

One of the key tasks in the field of radiovision consists in the detection and classification of objects in space. It is well known that recognizing the shape, size and radiophysical identifiers of objects in real time using neural network algorithms requires a combined approach to signal processing that harnesses the complementary strengths of neural network and machine learning (ML) approaches. In some cases, these technologies offer clear advantages over optimal processing methods [1]. The correct classification of objects based on their radio images, which exhibit a gradient, sharp transition, and heterogeneous surface structure, is critical in a number of scientific and practical areas. One example is the creation of synthetic aperture radars for small satellite constellations for Earth observation, such as the Kondor, which are designed for obtaining high- and medium-resolution radio images.[1]

Unlike the agreed methods of wavelet filtering of ultra-wideband signals in the frequency-time domain [2], modern solutions for radio image recognition focus more on processing data using ML technologies and neural network methods based on classifiable features. These methods do not require assumptions about the probability distribution of data [1]. Neural networks can be used to analyze multiple signal parameters simultaneously, thus significantly increasing processing speed and reducing the probability of error by 5–15%.

The paper explores the use of ML techniques, such as linear regression, classification and random forest, along with a neural network with a fully connected architecture, to recognize radio images of objects of various radiophysical natures, which are described by the superposition of basic stereometric shapes. The main focus is on comparing these methods and exploring the potential for combining them.

The neurovision study consists of three stages. The first stage involves creating a database of radio signal images using the *Ansys HFSS* electrodynamic simulation environment.[2] The second stage involves training ML models and creating a neurovision algorithm, as well as further training of the neural network. The third stage involves analyzing the accuracy of object classification and statistical criteria for radio image reproducibility.

The combined neurovision method proposed in this paper is of practical interest in the development of digital processing technologies for secondary signals from aerospace and ground-based radio visors. In such scenarios, given the limited computing resources available on board, it is essential to minimize the time taken by the algorithm for object recognition [3].

1. CREATING A DATABASE OF RADIO IMAGES FOR NEUROVISION TRAINING

In the context of ML methodologies or neural networks, the establishment of a database is imperative for training a particular model or architecture. The initial step therefore involves the creation and population of such a database with signal responses from designated objects. To conduct a software-numerical experiment involving the classification of objects by shape based on signal responses, a database of radio responses from basic shapes was prepared using the *Ansys HFSS* electrodynamic simulation environment [4].

The experimental model created in the *Ansys HFSS* environment to generate radio images is depicted in (Fig. 1). Horn antennas were synthesized to radiate and receive at frequencies between 0.5 and 2 GHz. These antennas are located equidistantly through a radio-absorbing partition, with the aperture rotated at an angle of 60° to the Y-axis. The object under study, represented by a basic stereometric figure, is placed on the line of sight (LOS) passing through the plane of the radio-absorbing partition at a distance corresponding to the Fraunhofer zone. Meanwhile, the receiving antenna detects the electrical component of the alternating field scattered by the basic figure's signature—that is to say, the radio signal image. Two types of scalable objects are selected for the experiment: five cube variants and five sphere variants. The cubes have edge lengths of 0.35, 0.4, 0.45, 0.5, and 0.55 m, respectively. The spheres have diameters of 0.35, 0.4, 0.45, 0.5, and 0.55 m, respectively. The base objects are stereometric figures with perfectly conductive surfaces.

The object signature is irradiated by a radiovision signal using a Gaussian monocycle model (Fig. 2) [4]. The monocycle generates an ultra-wideband spectrum ranging from 0.7 to 1.0 GHz, equivalent to wavelengths between 42 and 30 cm. The objects under study have scalable dimensions ranging from 35 to 55 cm.

The experimental model shown in Fig. 1 is used to register the signal scattered by the signature of a radio and television object. To do this, a Gaussian monocycle radiation pattern must be generated as shown in Fig. 2. The specified amplitude spectrum of the Gaussian monocycle is calculated in the *Ansys HFSS* electrodynamic simulation environment. Upon successful completion of the calculation, *Ansys HFSS* displays animations of frequency-time nomograms of the near and far fields, which demonstrate the propagation of radiovision

[1] User's Guide to Earth Remote Sensing Data Obtained by the Kondor-FKA Space System – 2023. *Nauchnyi Tsentr Operativnogo Monitoringa Zemli* (Scientific Center for Operational Monitoring of the Earth). https://ntsomz.ru/wp-content/uploads/2023/05/2023.02.17.rukovodstvo.pol_.zovatela.kondor-fka.dla_.saita_.pdf. Accessed August 14, 2025. (In Russ.).

[2] https://www.ansys.com/products/. Accessed August 14, 2025.

probing and scattered signals [5]. In the simulation, the animation calculation duration is set to 25 ns. Figure 3 shows freeze frames of four nomograms displaying the distribution of the electrical component of the scattered signal signature of a radiovision pulse field from:

- a cube with an edge length of 0.55 m at 4950 ps (Fig. 3a) and at 11010 ps (Fig. 3b);
- a sphere with a diameter of 0.35 m at 5520 ps (Fig. 3c) and at 12030 ps (Fig. 3d).

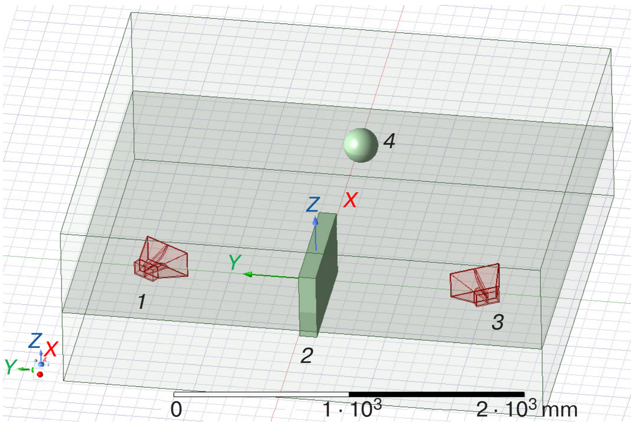

Fig. 1. Software-numerical electrodynamic model of the experiment on the formation of radio images of objects:
(*1*) receiving antenna,
(*2*) radio-absorbing partition,
(*3*) transmitting antenna, and
(*4*) radiovision object specified by the signature of the base figure

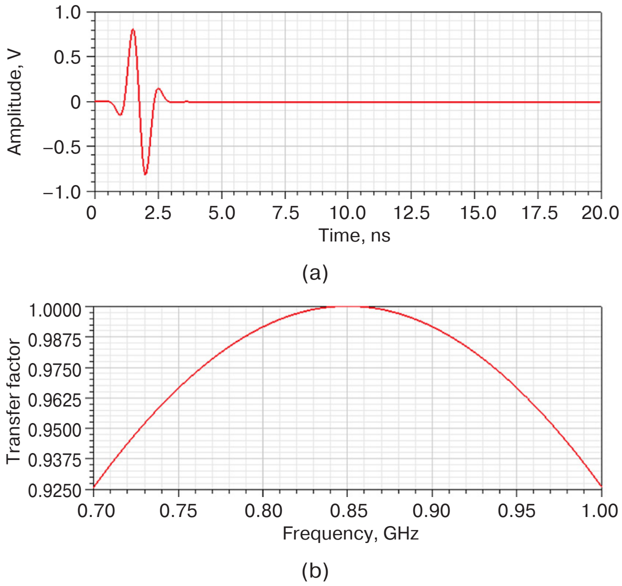

Fig. 2. Representation of a Gaussian monocycle in the time (a) and frequency (b) domains

In addition to animating nomograms of the propagation of incident and scattered components of electromagnetic fields, the model allows for the construction of radio profiles of the distribution of the scattered signature of an object's electric field in a selected direction. Figure 4 shows radio images of objects obtained through diffuse scattering by lateral surface inhomogeneities, with a cube having an edge length of 0.55 m and a sphere having a radius of 0.35 m [6].

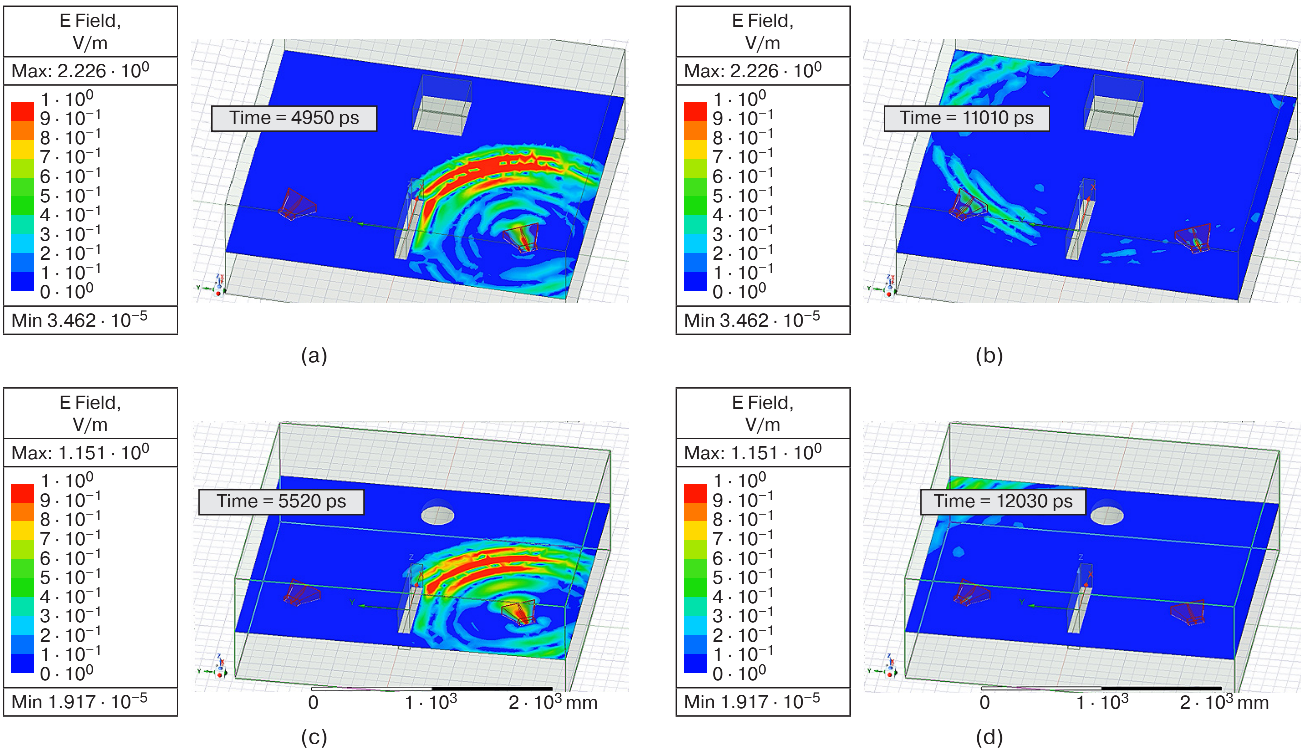

Fig. 3. Freeze frames of distribution nomograms scattered in the far zone of the field from a cube and a sphere

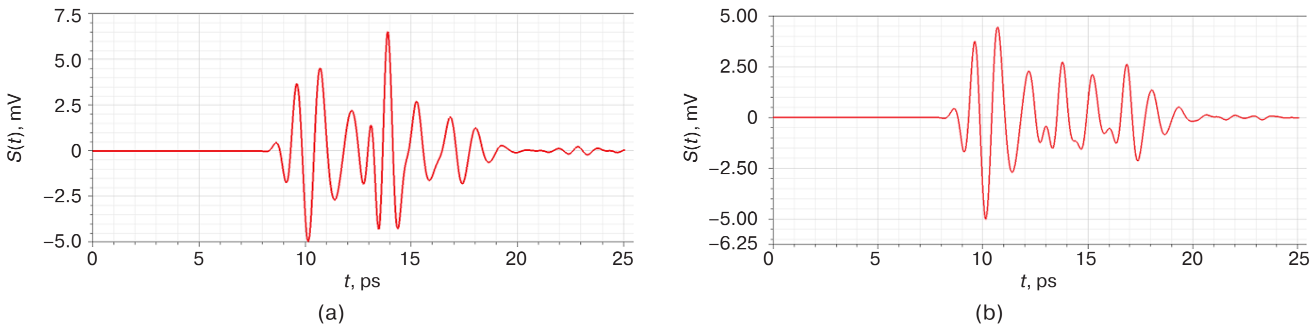

Fig. 4. Radio images of cubic (a) and spherical (b) objects, obtained from a given scattering direction determined by Snell's law

The radio images obtained can be exported from *Ansys HFSS* as a data sample comprising 965 instantaneous values of the reduced field strength in millivolts (mV), which are sampled at intervals of 0.025 ns. The arrays of software-numerical experimental values that make up the neurovision database, obtained for five spherical and five cubic objects with different form factors, are given in Table 1.

Table 1. Neurovision data of radio images with established form factors

Object type	Sphere (form factor *D*, m)					Cube (form factor *L*, m)				
Form factor	0.35	0.4	0.45	0.5	0.55	0.35	0.4	0.45	0.5	0.55
Time index with a step of 25 ps	Instantaneous dynamic values of impulse radio images, mV									
340	−0.0195	−0.0514	0.0945	0.1146	−1.7058	−1.5478	−0.8098	1.7553	0.3806	0.3287
341	−0.1693	−0.2056	−0.0405	−0.0189	−1.5988	1.3636	−0.4782	1.1756	−0.2834	−0.3413
342	−0.3451	−0.3844	−0.1967	−0.1740	−1.4304	−1.1189	−0.0748	0.5183	−0.9570	−1.0179
343	−0.5208	−0.5632	−0.3781	−0.3554	−1.2007	−0.7913	0.3640	0.5183	−1.6125	−1.6716
344	−0.7138	−0.7572	−0.5595	−0.5367	−0.8847	−0.4636	0.8264	−0.1699	−2.2679	−2.3252
345	−0.9105	−0.9534	−0.7567	−0.7349	−0.5687	−0.0658	1.2975	−0.8719	−2.8737	−2.9239
346	−1.1041	−1.1445	−0.9564	−0.9362	−0.1779	0.3665	1.7685	−1.5597	−3.4262	−3.4663
347	−1.2774	−1.3120	−1.1510	−1.1332	0.2514	0.8218	2.2189	−2.2475	−3.9123	−3.9395
348	−1.4506	−1.4796	−1.3222	−1.3076	0.7083	1.2854	2.6359	−2.8865	−4.2756	−4.2872
349	−1.5870	−1.6069	−1.4934	−1.4819	1.1808	1.7489	3.0048	−3.4709	−4.6389	−4.6349
350	−1.6879	−1.6966	−1.6241	−1.6166	1.6533	2.1925	3.2758	−3.9862	−4.8615	−4.8405
351	−1.7456	−1.7412	−1.7168	−1.7135	2.1131	2.6034	3.5468	−4.3722	−4.9819	−4.4429
…	…	…	…	…	…	…	…	…	…	…
963	−0.0575	−0.0021	−0.0202	−0.0125	−0.0124	−0.0505	0.0309	−0.0059	−0.0279	0.0012
964	−0.0501	−0.0085	−0.0173	−0.0177	−0.0102	−0.0434	0.0329	−0.0094	−0.0274	0.0008
965	−0.0501	−0.0134	−0.0173	−0.0222	−0.0102	−0.0434	0.0347	−0.0119	−0.0255	0.0008

The resulting neurovision database is comprised of a data frame in which the categories for the neural network model are radio images of objects, while the indices are instantaneous dynamic values of the signal radio profile. A special Python program was developed to represent and process the neurovision database of responses in a specified format using ML and neural network methods. The resulting database is entered into the program as a separate DataFrame data type using the Pandas module (a library for processing and analyzing structured data). This allows two-dimensional arrays of information containing both numerical and string data to be stored. The Pandas module additionally provides researchers with access to all stored data. Since it works with a copy of the original radio and television data, this module uses the computing device's memory resources to store and process information. This means that the information obtained in the form of a DataFrame can be used for ML and neural network methods [7].

2. ANALYSIS OF THE EFFECTIVENESS OF ML METHODS IN RADIO IMAGE RECOGNITION

As part of the conducted neurovision research, the prediction results obtained using three different ML methods are compared. The choice of algorithms is determined by the aim of covering classical linear models, as well as more complex non-linear and ensemble approaches. The selected algorithms are linear regression, a classification method based on the support vector machine, and a random forest method. Linear regression is chosen as the basic, interpretable method, while the classification method comprises a powerful algorithm for working with high-dimensional data, and the random forest method functions as a benchmark ensemble method that is resistant to overfitting [8]. The ML algorithm models are built using the scikit-learn Python library (an open-source library for predictive data analysis).

We consider the semantic characteristics of each algorithm, which are as follows:

A. In the case of the linear regression method, the equation $Y = aX + b$ is used, where a and b are coefficients that are determined during training [9]. However, since the output parameter must be a numerical integer, the values of the category names should be replaced; for example, "sphere" and "cube" are replaced with the features "1" and "2," respectively.

B. The classification method differs from regression mainly insofar as regression has no classes, so it is the possible value of the output parameter that is predicted. In contrast, classification has a strictly limited number of classes or categories, as does the sample used to provide an answer [10].

C. Random Forest is a more complex version of simple ensemble models (Fig. 5). The main difference from previous methods consists in the random selection of object features for training from the general database set and distributed into smaller subsamples (datasets). Furthermore, features of the same object may appear in several new subsamples [9]. Thus, unlike classical ensembles, which use a system of all possible features, the random forest method enables the selection of a feature on which the neural network model will be strictly based.

As shown in Fig. 5, the random forest method is notable for its ability to artificially boost the database of signal responses used for training, thereby minimizing the likelihood of neurovision recognition errors.

Five additional radio images of objects are obtained for comparison of the considered algorithms: three from spherical bases with form factors of 0.35, 0.375, and 0.4 m, and two from cubic bases with form factors of 0.45 and 0.475 m. The data is then loaded into a database of trained software models for evaluation of neurovision recognition accuracy and identification of error probabilities. Table 2 shows the results of the ML-based neurovision model for recognizing objects by form factor in the absence of interference.

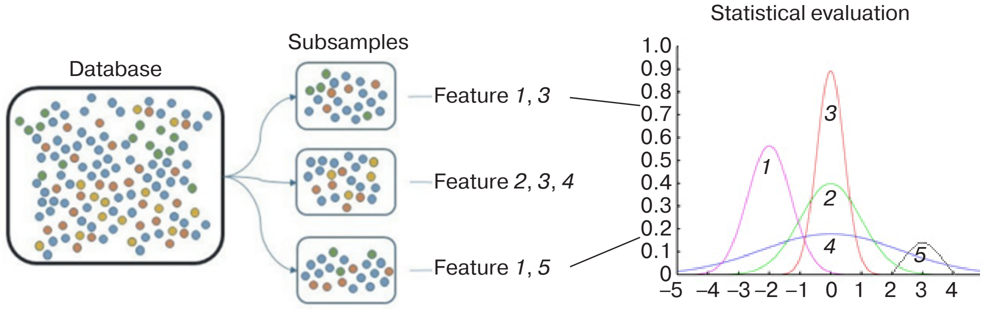

Fig. 5. Formation of datasets using the random forest method based on strictly selected spectral-temporal radiovision features

Table 2. Probability of correct classification for trained models of neurovision recognition of objects with a given form factor

Method	Linear progression	Classification	Random forest
Probability of correct classification	0.3	0.72	0.85

The study employs two complementary metrics to evaluate the effectiveness of ML models and neural networks: the correlation coefficient and the probability of correct classification.

The correlation coefficient (r) measures the similarity between the model's prediction and the reference sample, and is used as a threshold criterion to determine reliability. The established threshold value of $r = 0.9$ is decisive: if the calculated coefficient exceeds this value, the classification result is considered reliable and accepted as correct. Conversely, if $r < 0.9$, the result is deemed insufficiently reliable, suggesting a potential model error.

The probability of correct classification is defined as the share of test cases for which the correlation coefficient exceeds the threshold of 0.9. This metric, which reflects the model's overall ability to perform correct recognitions, is calculated as the ratio of the number of successfully classified examples (with $r \geq 0.9$) to the total test sample size, N_{total}:

$$P = N_{r \geq 0.9}/N_{\text{total}}.$$

The highest probability of correct classification achieved using the above ML methods is 0.85 for the random forest method. However, in the absence of sufficient training data, this value can lead to unsatisfactory results compared to wavelet analysis methods [11].

3. ANALYSIS OF THE EFFECTIVENESS OF NEURAL NETWORK APPLICATION IN RADIO IMAGE RECOGNITION

The developed neural network architecture is a fully connected, multilayer neural network consisting of three layers: two hidden layers and one output layer (Fig. 6) [12]. The network receives 965 instantaneous values of the reduced field strength in millivolts (mV) at a sampling rate of 25 picoseconds (ps). The first hidden layer, which consists of 16 neurons, converts the input signal from the received dimension into 16 features. The second hidden layer, consisting of eight neurons, converts the input signal from the 16 features into eight features. The output layer consists of one neuron that converts the input signal from eight features into one output value.

A three-layer fully connected neural network architecture is chosen to strike a balance between computational efficiency and model stability against overfitting with a limited amount of initial training data. Given the small size of the dataset, increasing the number of layers would significantly increase the number of trainable parameters and reduce the model's ability to generalize. Thus, the adopted architecture provides sufficient expressive power to extract feature hierarchies from radio signals while maintaining the computational efficiency required for real-time tasks.

The neural network is implemented using object-oriented programming principles.[3] A snippet of the code listing describing the neural network is shown in Fig. 7. This demonstrates the definition of a neural network class (Fig. 6) with three fully connected layers [13].

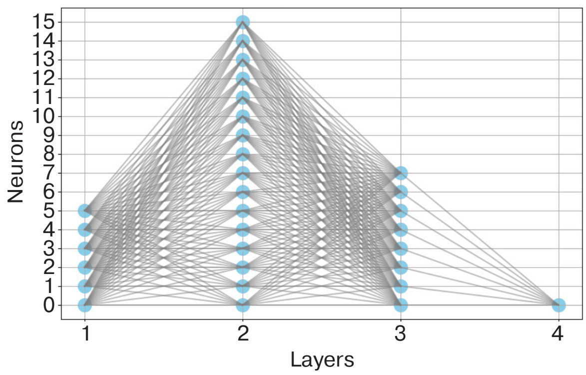

Fig. 6. Architecture of a neurovision network with three fully connected layers

The code initializes the weight matrices (**W1**, **W2**, and **W3**) and the bias vectors (**b1**, **b2**, and **b3**) with their respective dimensions. The forward function, which is a method of the neural network (NN) class, implements direct signal propagation through layers with rectified linear unit (ReLU) activation functions and a sigmoid function at the output.

The $\text{ReLU} = \begin{cases} x, & x > 0, \\ 0, & x < 0 \end{cases}$ operator is selected as the activation function for the neurons of the 1st and 2nd layers [14].

[3] Bosenko T.M. *Fundamentals of Object-Oriented Analysis and Programming in Python*: A study guide. Moscow: Moscow City Pedagogical University; 2023, 80 p. (In Russ.).

```
class NN:  1 usage
    def __init__(self, input_size):
        self.W1 = tf.Variable(tf.random.normal([input_size, 16]), name='weight1')
        self.b1 = tf.Variable(tf.zeros([16]), name='bias1')
        self.W2 = tf.Variable(tf.random.normal([16, 8]), name='weight2')
        self.b2 = tf.Variable(tf.zeros([8]), name='bias2')
        self.W3 = tf.Variable(tf.random.normal([8, 1]), name='weight3')
        self.b3 = tf.Variable(tf.zeros([1]), name='bias3')

    def forward(self, x):  3 usages (1 dynamic)
        z1 = tf.matmul(x, self.W1) + self.b1
        a1 = tf.nn.relu(z1)
        z2 = tf.matmul(a1, self.W2) + self.b2
        a2 = tf.nn.relu(z2)
        z3 = tf.matmul(a2, self.W3) + self.b3
        return tf.sigmoid(z3)

    @property  2 usages (2 dynamic)
    def trainable_variables(self):
        return [self.W1, self.b1, self.W2, self.b2, self.W3, self.b3]
```

Fig. 7. Code listing snippet describing a neural network

First and foremost, this is because the ReLU operator enables the processing of data arrays, offers computational efficiency, eliminates the issue of vanishing gradients, and encourages sparse activations.

The weight matrices **W1**, **W2**, and **W3** are initialized with random values and the bias vectors **b1**, **b2**, and **b3** with zeros.

The data is processed through the neural network in a sequential manner through three layers. In the first layer, the input data is transformed linearly by multiplying it by the weight matrix **W1** and adding the bias vector **b1**. After this, the ReLU activation function is applied to the resulting value. In the second layer, the output of the previous layer is again multiplied by a weight matrix **W2** and a bias vector **b2**. The ReLU activation is also applied. Finally, in the output layer, the features obtained are multiplied by a third weight matrix **W3** and a bias **b3**. The final value is then normalized using the sigmoid activation function to produce a probability value indicating the likelihood of belonging to a specific class [12].

The network is trained using the backpropagation error algorithm. Binary cross-entropy is used as the loss function to measure the difference between predicted probabilities and true labels. The trainable_variables function returns a list of all parameters that can be modified by the optimizer. The Adam (short for Adaptive Moment Estimation) optimizer is used, which is a hybrid optimization algorithm that adjusts the learning rate for each parameter based on estimates of the first and second moment gradients. This algorithm is effective for handling large datasets [15]. The training dataset has previously been augmented by 30% using the bagging ML method in the program [9].

The learning process involves the following stages:

- Forward pass: Calculating predictions for input values.
- Error calculation: Comparing predictions with true values.
- Backward pass: Calculating gradients, i.e., directions of parameter change [12].
- Updating weights: Adjusting network parameters to reduce error.

To remove the additional dimension from the predictions, a squeeze function is applied, which is essential for calculating losses correctly. This allows coordinating the dimensions of the tensors of predictions and ground truth values in order to calculate the loss function [16].

The evaluation of the model's prediction quality is carried out using the binary_crossentropy function. This function calculates the binary cross-entropy between the actual labels and the predicted values, which provides a measure of the discrepancy between two probability distributions. This metric can be used to evaluate the effectiveness of the model in binary classification tasks by quantifying the difference between the predicted probability distribution and the true label distribution.

The database of neurovision data derived from radio imaging of objects (Table 1) was used as the training

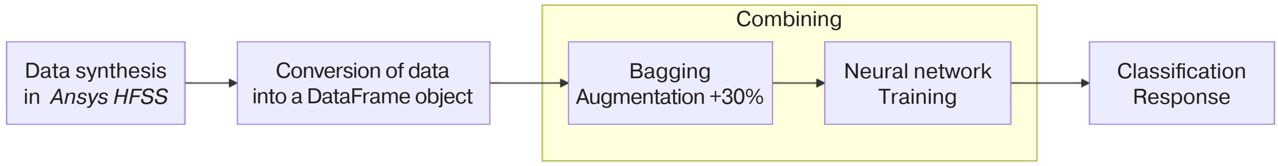

Fig. 8. Diagram of the combined algorithm for radio image recognition

dataset for the developed neural network model. To verify the accuracy of the calculations and access the generalizability of the model, a separate testing set of 5 radio images has been generated. The three images are from spherical objects with form factors of 0.35, 0.375, and 0.4 m; two images are from cubic objects with 0.45 and 0.475 form factors. In order to ensure the objectivity in the validation process, it is crucial that the testing objects with intermediate form factors of 0.375 and 0.475 m are not included in the training set. Although all data is generated in *Ansys HFSS*, the testing set consists of objects that are novel to the model. The neural network demonstrates a 0.97 accuracy rate on the independent testing set. This result is likely due to the fact that the training dataset is smaller than the desired. However, if the data sample is not artificially augmented using bagging, the same neural network's probability of correct classification would be only 0.93. This is a reduction of 0.04 compared to the original probability. This significantly improves the resulting accuracy of the model and demonstrates the efficacy of bagging in mitigating overfitting with small sample sizes.

Thus, the developed integrated algorithm implements a synergistic approach to radio imaging data processing by combining ML techniques with a neural network in a consistent manner. As shown in the diagram (Fig. 8), the procedure starts with the synthesis of source data in *Ansys HFSS*, which is then transformed into a DataFrame object. The key subsequent stage involves combining the bagging method for data augmentation with a fully connected neural network for classification. This allows the system to overcome limitations of a small initial sample size by artificially expanding the dataset and simultaneously utilizing the high recognition capabilities of the neural network model, resulting in high classification accuracy.

CONCLUSIONS

In the paper, a novel neurovision method has been developed and validated for recognizing radio signals from objects based on ML and neural networks. The method combines a fully-connected artificial neural network with a bagging ML approach, allowing for the real-time classification of basic stereometric shapes from radio images acquired in the centimeter-wavelength range. Experimental validation of the algorithm is conducted using a dataset of synthetic radio image signals generated by a custom software-based electrodynamic simulator in the *Ansys HFSS* environment. This enables the creation of a comprehensive dataset containing radio images of various objects with defined geometric properties. Using this database, the developed algorithm is able to recognize the objects utilizing a neurovision network consisting of three fully-connected layers and data augmentation techniques.

Based on a comparative analysis of ML techniques and neural networks, experimental findings have been obtained that confirm the effectiveness of the proposed integrated approach for radiovision tasks:

- The developed three-layer fully connected neural network with ReLU and sigmoid activation functions achieves a 0.97 probability of correct classification for spherical and cubic objects.
- It is shown that using data augmentation techniques such as bagging to increase the training dataset by 30% enhances the neural network's accuracy by 0.04, from 0.93 to 0.97, effectively addressing overfitting in small datasets.
- It is demonstrated that, out of the ML techniques under consideration, the random forest algorithm yields the highest probability of correct classification (0.85), which is 0.55 greater than that of linear regression (0.3) and 0.12 greater than the classification technique (0.72), although it is inferior to neural network approaches.
- The combined algorithm that combines the bagging approach with a neural network using data augmentation for classification can be used to achieve a 0.97 probability of correct classification.

The proposed combined approach, which demonstrates efficacy through the synergistic application of the ML algorithm (bagging) for data augmentation and a neural network for classification, successfully overcomes the limitations of each technique when applied individually. At the same time, this combined approach has several limitations, including dependence on the accuracy of synthetic data and the necessity to validate objects with intricate geometries under interference. These limitations determine the avenues for future research.

Authors' contributions

V.A. Kozhemyako—formulation of aims and objectives, practical research of the combined neurovision method and the algorithm for recognizing signal radio images.

A.D. Yarlykov—formulation of the research plan, formulation of conclusions.

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