Information systems. Computer sciences. Issues of information security

Информационные системы. Информатика. Проблемы информационной безопасности

UDC 004.93
https://doi.org/10.32362/2500-316X-2022-10-5-28-37

RESEARCH ARTICLE

Development of a neural network model for spatial data analysis

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Abstract
Objectives. The paper aimed to develop and validate a neural network model for spatial data analysis. The advantage of the proposed model is the presence of a large number of degrees of freedom allowing its flexible configuration depending on the specific problem. This development is part of the knowledge base of a deep machine learning model repository including a dynamic visualization subsystem based on adaptive web interfaces allowing interactive direct editing of the architecture and topology of neural network models.
Methods. The presented solution to the problem of improving the accuracy of spatial data analysis and classification is based on a geosystem approach for analyzing the genetic homogeneity of territorial-adjacent entities of different scales and hierarchies. The publicly available EuroSAT dataset used for initial validation of the proposed methodology is based on Sentinel-2 satellite imagery for training and testing machine learning models aimed at classifying land use/land cover systems. The ontological model of the repository including the developed model is decomposed into domains of deep machine learning models, project tasks and data, thus providing a comprehensive definition of the formalizing area of knowledge. Each stored neural network model is mapped to a set of specific tasks and datasets.
Results. Model validation for the EuroSAT dataset algorithmically extended in terms of the geosystem approach allows classification accuracy to be improved under training data shortage within 9% while maintaining the accuracy of ResNet50 and GoogleNet deep learning models.
Conclusions. The implemention of the developed model into the repository enhances the knowledge base of models for spatial data analysis as well as allowing the selection of efficient models for solving problems in the digital economy.

Keywords: neural network, deep learning, remote sensing data, geosystem, classification, machine learning

• **Submitted:** 20.12.2021 • **Revised:** 11.07.2022 • **Accepted:** 24.08.2022

For citation: Yamashkina E.O., Yamashkin S.A., Platonova O.V., Kovalenko S.M. Development of a neural network model for spatial data analysis. *Russ. Technol. J.* 2022;10(5):28–37. https://doi.org/10.32362/2500-316X-2022-10-5-28-37

Financial disclosure: The authors have no a financial or property interest in any material or method mentioned.

The authors declare no conflicts of interest.

НАУЧНАЯ СТАТЬЯ

Разработка нейросетевой модели для анализа пространственных данных

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Резюме

Цели. Цели настоящего исследования – разработка и апробация нейросетевой модели для анализа пространственных данных. Преимуществом предложенной модели является наличие большого количества степеней свободы, что позволяет гибко конфигурировать модель, исходя из решаемой проблемы. Данная разработка входит в состав базы знаний репозитория моделей глубокого машинного обучения, включающего подсистему динамической визуализации на основе адаптивных веб-интерфейсов с интерактивной возможностью прямого редактирования архитектуры и топологии нейросетевых моделей.

Методы. Решение проблемы повышения точности анализа и классификации пространственных данных основано на привлечении геосистемного подхода, предполагающего анализ генетической однородности территориально-смежных образований различного масштаба и иерархического уровня. Для апробации предложенной методики применен открытый набор данных EuroSAT, сформированный для обучения и тестирования моделей машинного обучения с целью эффективного решения проблемы классификации систем землепользования и растительного покрова с использованием спутниковых снимков Sentinel-2. Онтологическая модель репозитория, в который входит модель, декомпозируется на домены моделей глубокого машинного обучения, решаемых задач и данных. Это позволяет дать комплексное определение формализуемой области знаний: каждая хранимая нейросетевая модель сопоставлена с набором конкретных задач и наборами данных.

Результаты. Апробация модели для набора EuroSAT, алгоритмически расширенного с позиции геосистемного подхода, дает возможность повысить точность классификации в условиях дефицита обучающих данных в пределах 9%, а также приблизиться к точности глубоких моделей ResNet50 и GoogleNet.

Выводы. Внедрение созданной модели в репозиторий позволит не только сформировать базу знаний моделей для анализа пространственных данных, но и решить проблему подбора эффективных моделей для решения задач в области цифровой экономики.

Ключевые слова: нейронная сеть, глубокое обучение, данные дистанционного зондирования, геосистема, классификация, машинное обучение

• **Поступила:** 20.12.2021 • **Доработана:** 11.07.2022 • **Принята к опубликованию:** 24.08.2022

Для цитирования: Ямашкина Е.О., Ямашкин С.А., Платонова О.В., Коваленко С.М. Разработка нейросетевой модели для анализа пространственных данных. *Russ. Technol. J.* 2022;10(5):28–37. https://doi.org/10.32362/2500-316X-2022-10-5-28-37

Прозрачность финансовой деятельности: Авторы не имеют финансовой заинтересованности в представленных материалах или методах.

Авторы заявляют об отсутствии конфликта интересов.

INTRODUCTION

Machine learning technologies including those based on deep neural network (DNN) models can be used to conduct high-precision automated monitoring of natural resource management (NRM) systems and analyze regularities of natural processes and phenomena. Here, a relevant scientific problem involves classification of land use (LU) and land cover (LC) system types on the basis of high-resolution remote sensing data. For this, deep machine learning (DML) methods and algorithms are applied under conditions of small quantities of labeled data obtained using the geosystem approach involving the genetic uniformity analysis of territorially adjacent entities of various scales and hierarchies.

The described geosystem territorial analysis model is characterized by a large number of degrees of freedom, allowing flexible tool configuration based on the current task and analyzed data. The proposed development is a part of the repository knowledge base of DML models including a dynamic visualization subsystem based on adaptive web interfaces offering interactive capability for directly editing the architecture and topology of neural network models (NNMs).

The NNM repository can be used not only to create a knowledge base for spatial data analysis but also to select efficient algorithms for solving problems arising in the digital economy. By decomposing the ontological model into domains of DML models, current tasks, and data, a comprehensive definition of the formalizing knowledge domain can be provided with each stored NNM being mapped to the set of specific tasks and datasets.

METHODOLOGY AND RESEARCH METHODS

DML can be used to reduce research costs when conducting spatial data analysis due to the possibility of accurate interpolation and extrapolation of measurements. The key to solving these problems is sought not only through improvements to the architecture of DML models, but also in developing methods and algorithms for the optimal enrichment of training datasets [1–3]. The present authors propose the use of a geosystem approach in which the state and properties of each territorial unit are determined by the features of its interaction with neighboring units. It is shown in [4] that a landscape has horizontal, vertical, and temporal structures; the vertical structure implies dividing the landscape into geohorizons, while the horizontal structure divides the landscape into facies and the temporal structure is related to the dynamics of landscape states.

This approach involves the assumption that land classification accuracy based on remote sensing could be increased by using a neural network to analyze not only the particular features of a system but also the features of the areas with which it interacts. In order to test this hypothesis, several datasets for model training should be prepared [5], including a basic (consisting of labeled areas fixed using satellite imagery) and extended (supplemented with data on neighboring and adjacent geosystems) dataset.

The methodology of spatial data analysis using DML and the formation of a DNN model comprising part of the repository and capable of efficiently analyzing the data can be described as follows. The graphical web interfaces of the DNN model repository justified in terms of UX system analysis allow a relevant machine learning model to be selected for solving specific tasks of spatial data analysis as well as obtaining systematized information on the required DNN model.

Figure 1 depicts the ontology model of the repository decomposed into DML model, project task, and spatial data domains. This allows the formalizing knowledge domain to be comprehensively defined as follows: each stored NNM is mapped to the set of specific tasks and

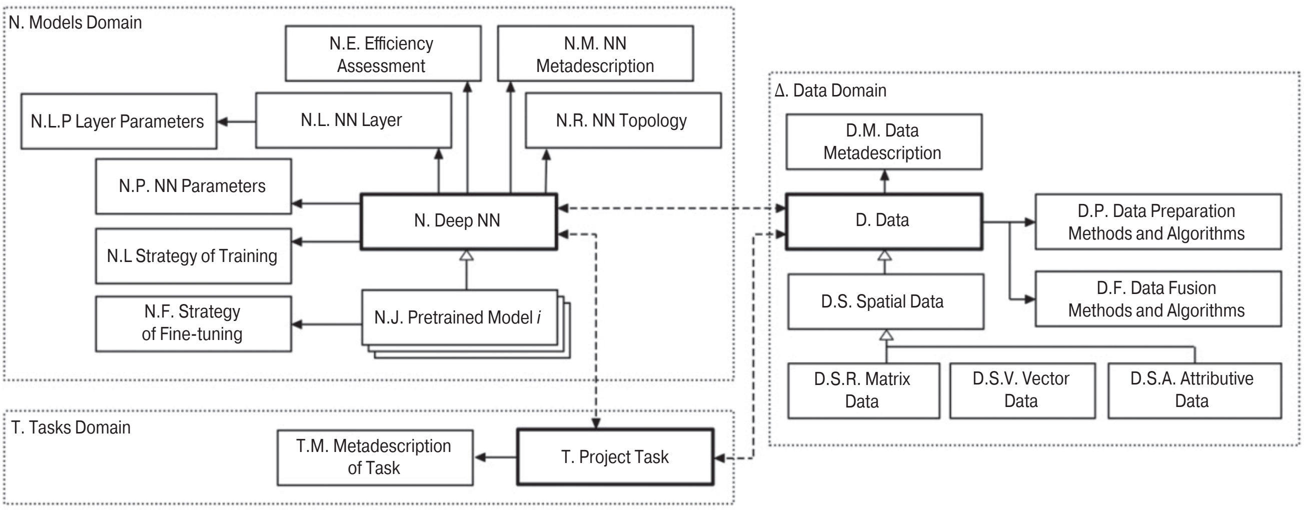

Fig. 1. Repository data model

datasets. This kind of system structure allows relevant searches for the most efficient architectural solution and fine tuning for solving project tasks to be carried out through the graphical web interface of the neural network repository.

The model storage scheme allows models to be converted into representations used by machine learning frameworks in order to integrate and use neural networks. In terms of the set-theoretic approach, the set of models of the *MODELS* repository comprises the universal set whose cardinality is determined by the number of repository models as follows:

$$MODELS = \{MODEL_i | 1 \le i \le N \wedge i \in \mathbb{Z}\}.$$

The topology of NNM $MODEL_i$ may be presented in the form of graph-scheme $GRAPH_i$ and structured meta-description $META_i$ (including the tuple of model parameters $COMPILATION_i$ describing methods and algorithms for NNM optimization as well as operating parameters). The $GRAPH_i$ element is an oriented graph where the vertex set $LAYERS_i$ defines the set of model layers while the arc set $LINKS_i$ defines the network topology for establishing connections between the layers, as follows:

$$MODEL_i = \langle META_i, GRAPH_i \rangle = \\ = \langle META_i, \langle LAYERS_i, LINKS_i \rangle\rangle.$$

The key component of the graph model i is the layer $LAYER_{ij}$, which can be represented as a set of objects defining the architecture of the layer set $TYPE_{\mathrm{layer}_{ij}}$, the interface set $INTERFACES_{ij}$, and arguments $PROPERTIES_{ij}$, as follows:

$$LAYER_{ij} = \langle TYPE_{\mathrm{layer}_{ij}}, INTERFACES_{ij}, PROPERTIES_{ij} \rangle.$$

During model training, the $TYPE_{\mathrm{layer}}$ object specifies data processing features and hyperparameter settings, as well as defining the layer architecture. The interface $INTERFACES_{ij}$ parameters of layer $LAYER_{ij}$ (of inputs $INPUTS_{ij}$ and outputs $OUTPUTS_{ij}$) are defined by tuple <*name*, *type*>, where *name* specifies the interface name while *type* specifies the dimension and data type.

$$INTERFACES_{ij} = \langle INPUTS_{ij}, OUTPUTS_{ij} \rangle = \\ = \langle \{INPUTS_{ij\lambda} | 1 \le \lambda \le \Lambda \wedge \lambda \in \mathbb{Z}\}, \\ \{OUTPUTS_{ij\mu} | 1 \le \mu \le \mathrm{M} \wedge \mu \in \mathbb{Z}\}\rangle.$$

The set $PROPERTIES_{ij}$ defines hyperparameters describing the layer $LAYER_{ij}$ features. This set of named arguments may include the definition of algorithms for weight initialization, regularization, and activation.

Taking tensors of data of different hierarchies on the classified territory and its host geosystems as inputs, DNN *MODEL* is designed for classifying spatial data. In terms of the black box, the deep classification model based on the geosystem approach comprises the functional element, whose input comprises images of the territory and its host geosystems obtained from satellite imagery, as well as synthetic maps [6, 7]. The number of inputs *INPUTS* may vary depending on the number of levels of the territory geosystem model. However, the temptation to increase them should be avoided since this would inevitably entail the need to increase the model capacity. The model has one output in the shape of vector with each *i*-th element determining the predicted probability of the territory belonging to the *i*-th category. The final hypothesis that the territory belongs to a certain category is made according to “the winner takes all” principle implying the object belongs to the class for which the model predicts the maximum probability. We now turn to the decomposition of the model.

The structure of each block is represented by the layer chain *LAYERS*. The first layer, which carries out depthwise separable convolution, allows features to be extracted from the original image, as well as making the model more compact and consequently resistant to retraining. This contrasts with using a conventional convolutional layer. The depthwise separable convolution having a kernel $\mathbf{W}$ of size K, which underlies the layer’s functionality, comprises the linear transformation. Each value $y_{i,j}$ of the output matrix $\mathbf{Y}$ is calculated based on values x of the original matrix $\mathbf{X}$, according to the following formula:

$$y_{i,j} = \mathbf{W} \bullet \mathbf{X} = \sum_{a=0}^{K-1} \sum_{b=0}^{K-1} \mathrm{W}_{a,b} x_{i+a,j+b}.$$

The convolution operation has important properties: as well as preserving the structure and geometry of the input, it is characterized by sparsity and multiple use of the same weights. The depthwise separable convolution deals not only with spatial dimensions, but also with depth measurements, such as image channels. Unlike conventional convolution, this involves using separate convolution kernels, on the basis of which two convolutions—depthwise and pointwise—are sequentially applied to the original tensor.

When solving the classification test problems described below, split testing of models with classical convolutional layers and depthwise separable convolution was performed to confirm the efficiency of the second approach. The batch normalization layer [8] providing regularization and stability of the model was the next layer of the feature extraction block to be efficiency-tested experimentally [9, 10]. The function ReLU[1] [11] performing the transformation of the form $x = \max(0, x)$

[1] https://pytorch.org/docs/stable/generated/torch.nn.ReLU.html. Accessed July 27, 2022.

was selected for activation. The feature extraction block is completed by the subsampling layer having external outputs and applying the maximum operation for reducing the size of the resulting representations. The experiments have shown the best result shown by applying the maximum operation. It is proposed that the number of output filters in convolution and the size of the convolution kernel be selected according to the principle of minimization of these values while maintaining acceptable classification accuracy. With every additional step comprising extraction of next-level features, the number of output filters for depthwise separable convolution should be increased.

The next model component block is the feature fusion module. This takes as input the features of level *N* extracted from the image of the classified territory along with geosystem images associated with it. The fusion modules of the second and subsequent levels also take as input the output data of the previous fusion module. All input data is concatenated into the single tensor and processed using the feature extraction pipeline, which consists of the layers of depthwise separable convolution, batch normalization, and activation and subsampling.

The output of the last feature fusion module is transformed into the vector and fed to the multilayer perceptron (MLP) input. The number of MLP dense layers and their capacity is selected according to the principle of minimization of these parameters while maintaining sufficient classification accuracy. In addition, applying batch normalization and thinning to the dense layer outputs is recommended for solving the overtraining problem. The function ReLU is selected for activating the output of the input and hidden layers with Sigmoid [12] for binary classification and Softmax [12] for multiclass classification selected for the output layer.

When training the classifier, the RMSProp algorithm[2] based on the stochastic gradient descent (SGD) method is used as the optimizer, while cross-entropy is used as the loss function. Fine-tuning of the model is influenced by the features of the particular classification problem being solved [13]. We now proceed to the model validation.

MODEL VALIDATION

The publicly available EuroSAT [14] dataset intended for training and testing machine learning models for effectively solving the problem of LU/LC system classification using Sentinel-2 satellite images[3] was used for initial validation of the proposed methodology [15]. The dataset, which is evenly divided into 10 classes (annual crops; forest; herbaceous vegetation; highway; industrial; pasture; permanent crop; residential; river; water), consists of 27 000 images containing information on areas distributed across the European Union in 13 spectral bands. Each element of the dataset, which has a size of 64 × 64 pixels and a spatial resolution of 10 m per pixel, is also characterized by georeferencing.

The characteristics of comparing the classification accuracy of different models for the EuroSAT dataset [16] based on different ratios of training and test samples are as follows. The ResNet-50 neural network model [17] shows the accuracy of 96.43% (for separating training and test data at the ratio of 80 to 20) and 75.06% (at the ratio of 10 to 90). The small convolutional network having two layers achieves an accuracy of 87.96% (80 to 20 splitting) and 75.88% (10 to 90 splitting). DML models based on convolutional layers show predominantly higher accuracy than support vector machines (SVM).

While modern deep convolutional networks offer excellent classification accuracy of satellite images with a relatively large size of the EuroSAT dataset training sample, these approaches entail significant accuracy losses under conditions of training data shortage. Thus, the problem of increasing the accuracy of methods and algorithms for spatial data analysis under their shortage remains a relevant research topic.

The data augmentation process is potentially subject to full automation. In the presence of information on geographic coordinates (latitude and longitude) of the classified area, the spatial data provider API can be requested for the fragment of satellite image including these coordinates and characterized by the required scale and resolution. In this way, it becomes possible to expand the training dataset algorithmically by importing the fragments of spatial imagery characterizing geosystems of a higher hierarchical level and containing the classified area.

Today, spatial data is publicly available via many Internet providers, some of which offer convenient application program interfaces (APIs) for fast retrieval [18, 19]. However, the low cost of this data is due to its poor temporal resolution (often, there is no possibility of selecting the specific date of spatial imagery). At the same time, this does not cease to be an informative source of information on host geosystems of different hierarchies. In the paper, the Mapbox API[4] is used by the authors for automated augmentation of the original dataset by satellite images of different scales.

The comparative accuracy values of the proposed model and CNN (2 layers) [12], ResNet-50, and GoogleNet [20] are presented in the Table. When

[2] Hinton G., Srivastava N., Swersky K. *Neural networks for machine learning. Lecture 6a. Overview of mini-batch gradient descent*. URL: http://www.cs.toronto.edu/~hinton/coursera/lecture6/lec6.pdf. Accessed July 27, 2022.

[3] https://sentinel.esa.int/web/sentinel/missions/sentinel-2. Accessed July 27, 2022.

[4] https://docs.mapbox.com/api/overview/. Accessed July 27, 2022.

Table. Classification accuracy of different models for the EuroSAT dataset

Method	Number of modules	Dataset	Testing range								
			10/90	20/80	30/70	40/60	50/50	60/40	70/30	80/20	90/10
CNN (2layers)	422 378	EuroSAT	75.88	79.84	81.29	83.04	84.48	85.77	87.24	87.96	88.66
ResNet-50	25 636 712	EuroSAT	75.06	88.53	93.75	94.01	94.45	95.26	95.32	**96.43**	**96.37**
GoogleNet	6 797 700	EuroSAT	77.37	90.97	90.57	91.62	**94.96**	**95.54**	**95.70**	96.02	96.17
Developed model	1 324 526	Extended EuroSAT	**86.23**	**91.52**	**93.98**	**94.11**	94.29	94.35	94.41	94.65	95.30

extracting test data from the EuroSAT dataset at a ratio of 40% and below, the proposed model shows the best result; the relative efficiency increases with the training sample decreasing as low as 10% (86.23% vs. 77.37% for the second result (GoogleNet)). With increased training data size, the model starts falling behind ResNet-50 and GoogleNet with the gap within the 2% range.

The developed model allows such results to be obtained due to the analysis of the EuroSAT dataset extended in terms of geosystem approach (while ResNet-50 and GoogleNet models been training and analyzing the original EuroSAT dataset). The difference in experimental conditions is negated by the low cost and rapidity of the fully automated training set expansion process, as well as by the lower model capacity: 1.3 mln units vs. 6.8 mln for GoogleNet and 25.6 mln for ResNet-50. Thus, the gained advantage in model training under data shortage is due to the low-cost automated geosystem-based expansion of the dataset and creation of an efficient model for its analysis.

Since training of neural networks is a probabilistic process, a series of 10 experiments was conducted to analyze the model training process, plotting the dependence of mathematical expectation and standard deviation of the classification accuracy on validation data on the training epoch. At early stages of the training process, the model demonstrates low classification accuracy of the extended set, which starts increasing from almost zero. The two-layer convolutional neural network and the ResNet-50 model may achieve above 40% accuracy from the first epoch. However, the developed model outperforms other models following the tenth training epoch to achieve the expected accuracy of 86%. A small standard deviation from the dependence mathematical expectation typical for training on small dataset should additionally be noted. This indicates greater stability of the model training process and high capability of generalizing information on the analyzed features correctly.

We now consider the cases of the developed model showing lower accuracy. The confusion matrix is shown in Fig. 2. Low matching values for such classes as "highway," "industrial," and "water" are due to the consideration of surrounding geosystem images during classification inevitably resulting in the increasing volume of data under analysis that may require a larger model capacity. Moreover, additional images may mislead the classification model in a number of cases; in terms of algorithm, it is definitely much easier to classify a single homogeneous image of water surface than an image supplemented by several fragments of smaller scale including coastal territories.

Thus, extending the EuroSAT dataset in terms of the geosystem approach and developing the model allows improving the classification accuracy under training data shortage (dividing the training set into the training and testing datasets at a ratio ranging from 10/90 to 40/60) as well as showing results exceeding the accuracy values of DML models while classifying the EuroSAT dataset.

CONCLUSIONS

Comprising part of the knowledge base of the repository of DML models, the developed neural network model allows the accuracy of analysis and classification of spatial data to be improved using a geosystem approach involving the genetic uniformity analysis of territorially adjacent entities of different scales and hierarchies. The repository may be deployed not only to create a model knowledge base for spatial data analysis but also to select efficient models for solving problems arising in various areas of the digital economy. The main advantage of the proposed model the high number of degrees of freedom it supports, which allows greater flexibility when configuring the model according to the particular problem to be solved.

The validation of the model according to the EuroSAT dataset algorithmically extended in terms of the geosystem approach shows the possibility of improving the classification accuracy under training

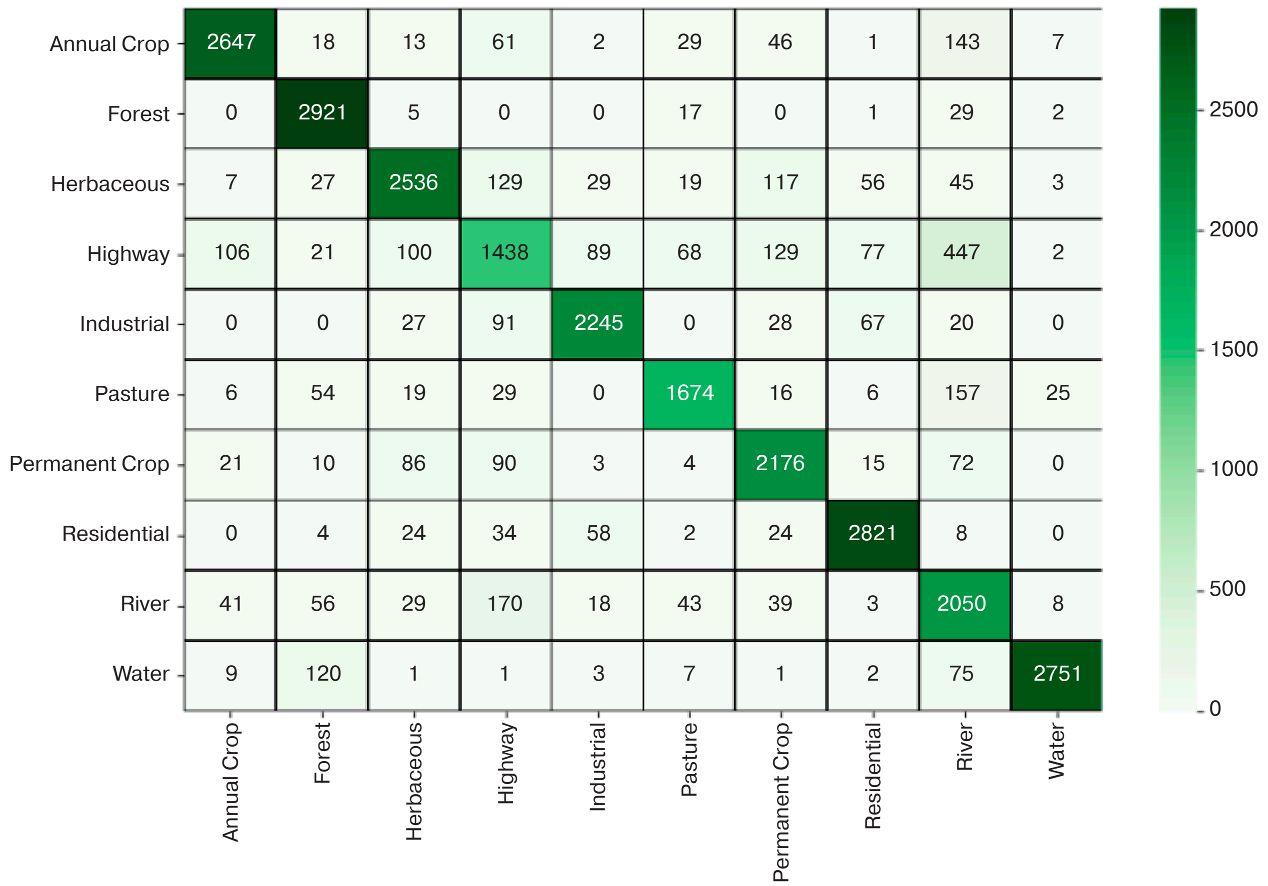

Fig. 2. Confusion matrix

data shortage within 9% while maintaining accuracy comparable with the ResNet50 and GoogleNet deep models. Following the tenth epoch of training, the developed model outperforms other models to achieve an expected accuracy of 86%.

ACKNOWLEDGMENTS

The study was supported by the grant from the President of the Russian Federation, project No. MK-199.2021.1.6).

Authors' contributions

E.O. Yamashkina—development and description of the research methodology, conducting experiments, and model optimization.

S.A. Yamashkin—statement of the problem and justification of the research concept, design and development of a neural network model.

O.V. Platonova—analysis of domestic and foreign experience in the field of interpretation of spatial data, work with the material, editing and preparation of the manuscript.

S.M. Kovalenko—planning of the experiment, interpretation and generalization of the results of the study.

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Translated from Russian into English by Kirill V. Nazarov
Edited for English language and spelling by Thomas A. Beavitt