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A method of neural network identification of thermokarst formations in Central Yakutia using graphic data from satellite remote

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Abstract

This paper presents a method for identifying thermokarst formations in Central Yakutia using remote sensing satellite images based on neural network technology. The method and methodology for generating data sets for training and testing neural networks containing four classes of landscape types, such as landscapes containing thermokarst formations, fields, forests and water bodies, are described. The structure and mathematical description of the convolutional neural networks forming the basis of the method for identifying thermokarst features are presented. The results of numerical experiments on the study of the accuracy of identification of satellite images of thermokarst formations and other landscape classes using the developed applied computer program are presented. Based on an analysis of the results of numerical experiments, three convolutional neural network models were selected that yield the best results in identifying thermokarst features, with accuracy levels of approximately 0.94–0.96.

Key words: convolutional neural networks, machine learning, thermokarst formations, satellite images, training datasets.

1 Introduction

A significant portion of the Earth's landscapes consists of cryolithozones characterized by active thermokarst degradation. While these processes have always occurred, the well-known trend of global warming has driven an unprecedented acceleration and intensification of them over the past 30 years, leading to catastrophic phenomena. These phenomena are particularly pronounced in Central Yakutia, manifesting as distinctive polygonal thermokarst formations (Fig. 1).



Fig. 1. Satellite image of thermokarst formation in Central Yakutia.

The rate of formation of such features in Central Yakutia has accelerated dramatically in recent decades, with an average formation period of 25–30 years [1–4]. In our view, insufficient attention is currently being paid to developing and refining methods for monitoring landscape degradation processes using machine learning technology. Several studies can be noted regarding the Arctic regions of Alaska, Canada, and Russia [5–7] and the mountainous landscapes of Tibet [8, 9], which address the segmentation of sinkholes and landslides, as well as a number of studies on Central Yakutia [10–13] that examine the identification of thermokarst features and the segmentation of thermokarst lakes [14].

2 Datasets

Given the aforementioned trends in the evolution of cryolithozone landscapes, improving methods for identifying thermokarst formations at their early developmental stages has become a task of exceptional practical importance and relevance. This paper presents a new method for the automated identification of thermokarst features using neural networks. The method relies on training a neural network to classify landscape types based on satellite imagery datasets from Google and Yandex mapping services (Fig. 2). A convolutional neural network was trained to recognize four landscape classes: areas containing thermokarst formations, forests, fields, and water bodies. Where necessary, thermokarst formations were verified using unmanned aerial vehicles (UAVs) [11].

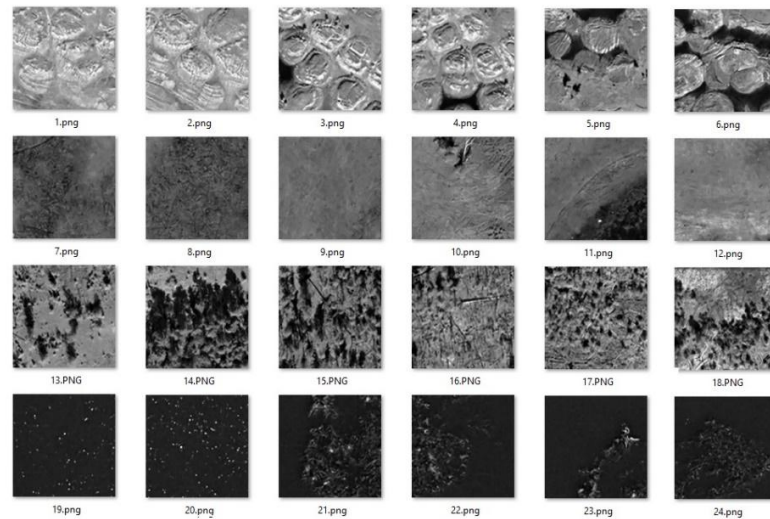


Fig. 2. Sample images of various landscape classes included in the training datasets.

An online application was developed to rapidly generate datasets by allowing users to select areas with different landscape classes on a map. This program was used to create datasets from images of areas in the Churapchinsky district of the Republic of Sakha (Yakutia), where numerous thermokarst formations are observed, as well as the village of Vladimirovka in the Yakutsk urban district.

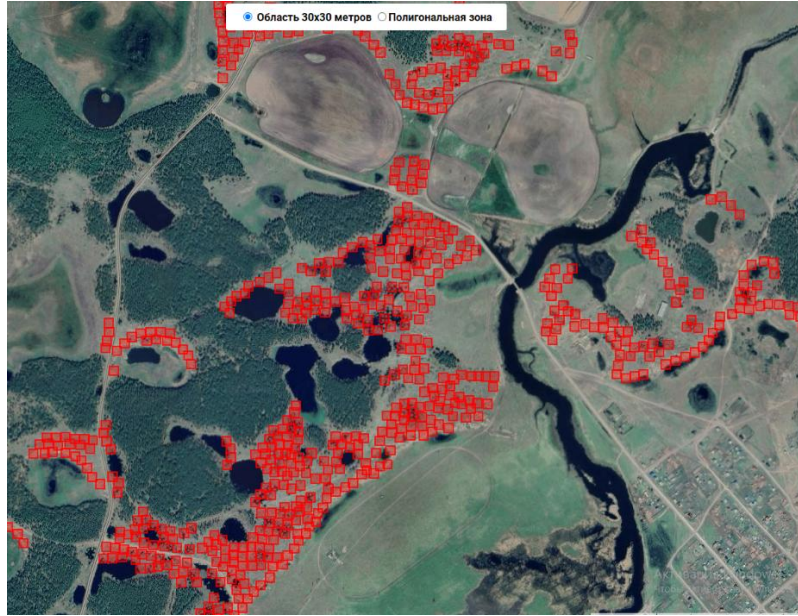


Fig. 3. Example of selected areas containing thermokarst features (red squares) in an online system for rapid dataset generation.

Two experimental datasets, DS0 and DS1, were created, containing images with dimensions of 70×70 pixels and 128×128 pixels (32×32 m), respectively (Table 1). An application was developed to organize the images, with data stored on an MS SQL Server. Dataset DS0 consists of 3,204 images, while DS1 contains 10,044 images.

Table 1. Training and testing datasets

N	Sets\classes	Thermokarst features	Fields	Forest	Water bodies
Dataset DS0					
1	Training subset	1242	1242	0	0
2	Validation subset	360	360	0	0
Dataset DS1					
1	Training subset	1746	2004	1305	1770
2	Validation subset	470	506	360	360
3	Test subset	308	704	151	360

3 Neural networks and an applied research program

To implement the convolutional neural network, an application was developed in Python using the capabilities of the TensorFlow machine learning library [12]. The program implements a convolutional neural network with a sequential architecture (Fig. 4).

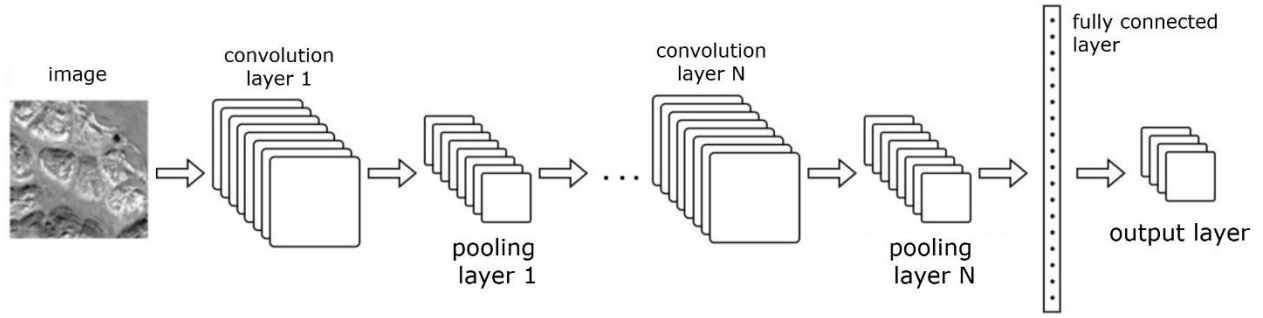


Fig. 4. Structure of a convolutional neural network.

The network consists of a series of convolutional and pooling layers and a final fully connected layer. In convolutional layers, the kernel will move across the image, highlighting certain features of it, i.e.

$$C(k, l) = (I \cdot K)(k, l) = \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} I(k+i, l+j) \cdot K(i, j) \quad (1)$$

where, I – image with dimensions k и l , K – core with dimension $m \times n$.

We apply the ReLU activation function to the result of the convolution operation:

$$C_a(k, l) = \max(0, C(k, l)) \quad (2)$$

In the subsampling layer, the dimensionality of the feature map is reduced by a factor equal to the size of the pooling window d :

$$C_{2d}(k, l) = \max(C_a(k \cdot d + a, l \cdot d + b)) \quad (3)$$

where, a and b are the matrix shift coefficients $C_a(k, l)$.

Next, the feature maps are fed into the final block of fully connected layers. *SparseCategoricalCrossentropy* was selected as the loss function:

$$L(y, y^*) = - \sum_{i=1}^N y_i \cdot \log(y_i^*) \quad (4)$$

where, y and y^* - are arrays of correct and predicted answers across N output classes.

The neural network training algorithm used in the numerical experiments is based on the backpropagation method [15], while the Adam method [16] was employed to optimize the learning rate. The network hyperparameters were selected based on the need for parameters that are simple and computationally inexpensive. The number of training epochs in the numerical experiments was empirically set to 150. To facilitate the numerical experiments, the developed application features a user interface; its main window is shown in Fig. 5.

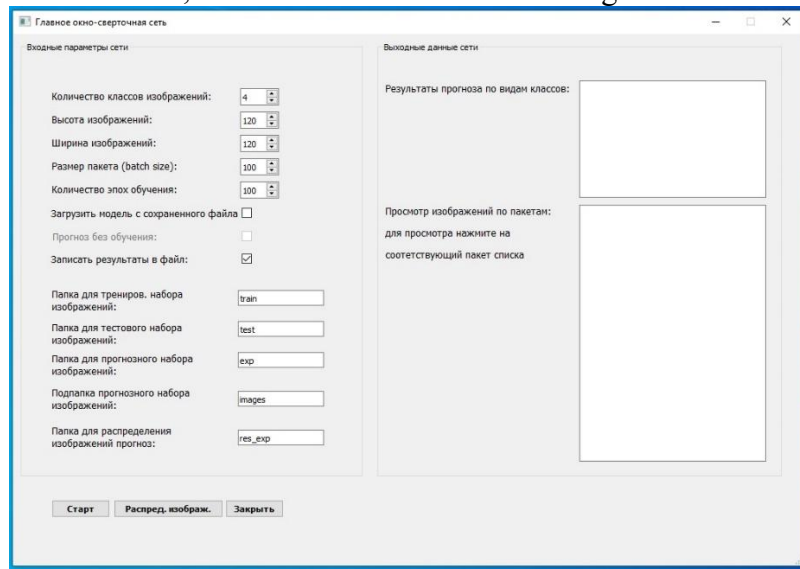


Fig. 5. Main window of the applied research program.

As the neural network transitions from one convolutional layer to the next, feature maps characteristic of each image class are formed, enabling them to be individually identified. Figure 6 shows the sequence of the layer-by-layer generation of a feature map of thermokarst formations using a convolutional neural network. It can be seen that, at layers 9 through 11 (excluding subsampling layers), simplified feature maps emerge for landscapes containing thermokarst formations. Figure 7 displays feature maps for thermokarst formations, fields, water bodies, and forests at the seventh layer of the convolutional neural network. It is evident that significant differences between the feature maps of the classes under consideration begin to manifest as early as the fourth layer.

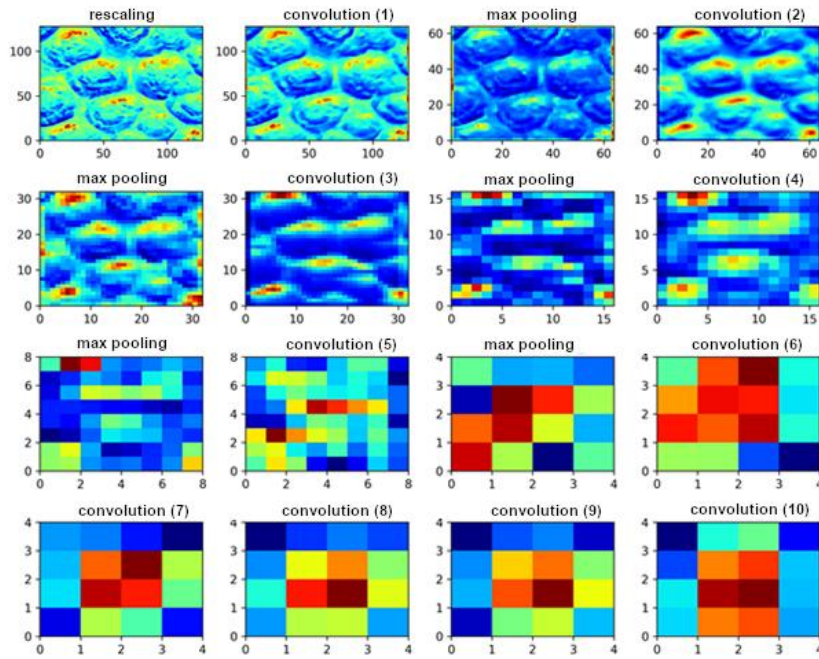


Fig. 6. Sequence of the layer-by-layer generation of a feature map of thermokarst formations by a convolutional neural network.

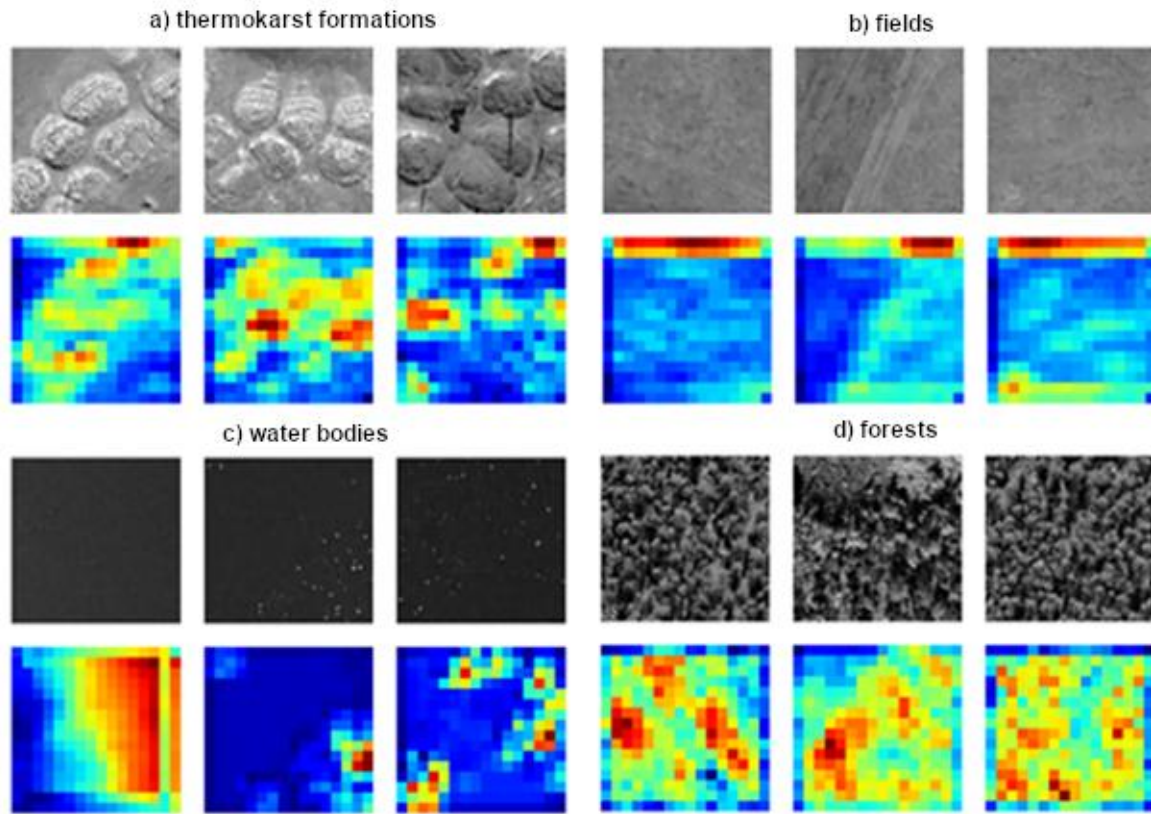


Fig. 7. Feature maps of thermokarst formations, fields, water bodies, and forests at the subsampling layer of the fourth layer of the convolutional neural network.

4 Neural network accuracy

To evaluate the accuracy of neural networks in identifying landscape images containing thermokarst features, a series of numerical experiments was conducted using various neural network models. Initially, experiments were performed using the balanced dataset DS0 (Table 1). For this dataset, the convolutional network's accuracy in identifying thermokarst features proved quite high for both the training and validation subsets, reaching up to 1.0 for the former and 0.97–0.98 for the latter. For the test subset, the accuracy was lower, ranging from 0.94 to 0.97. Subsequently, the task complexity was increased, and experiments continued using the unbalanced dataset DS1 (Table 1). In total, 17 series of numerical experiments were conducted using dataset DS1 (Table 2), involving approximately 180 different convolutional neural network models. Table 2 presents the model series investigated, using the notation format $N \times Mc$, where N denotes the number of layers (excluding subsampling layers), M denotes the number of filters, and c indicates a convolutional layer. For example, $2 \times 64c$, $N \times 32c$, 256 denotes a network consisting of 2 convolutional layers with 64 filters, N convolutional layers with 32 filters, and one fully connected layer with 256 nodes (neurons).

Table 2. List of model series

№	Network model series	Number of layers
1	$128c, 64c, 32c, 128$	4
2	$128c, 64c, 32c, 256$	4
3	$N \times 128c, 256$	4-6
4	$N \times 128c, 256c, 256$	4-7
5	$N \times 32c, 256$	5-7

6	$N \times 64c, 2 \times 32c, 256$	7-8
7	$2 \times 64c, N \times 32c, 64$	7-8
8	$N \times 32c, 128$	5-8
9	$N \times 64c, 128$	5-8
10	$N \times 32c, N \times 64c, 128$	5-8
11	$64c, N \times 32c, 128, 128$	5-8
12	$2 \times 64c, N \times 32c, 256, 128$	5-8
13	$2 \times 64c, N \times 32c, 2 \times 256, 128$	5-8
14	$2 \times 64c, N \times 32c, 512, 256, 128$	5-8
15	$2 \times 32c, N \times 64c, 128$	5-18
16	$2 \times 64c, N \times 32, 128$	5-18
17	$2 \times 32c, 2 \times 64c, N \times 128c, 128$	5-17

In the numerical experiments conducted using the imbalanced dataset DS1, accuracy metrics were determined as follows:

$$Recall = \frac{TP}{TP + FN}, \quad (5)$$

$$Precision = \frac{TP}{TP + FP}, \quad (6)$$

$$F1 - score = 2 \times \frac{Recall \times Precision}{Recall + Precision}, \quad (7)$$

where

TP - true positive results;

FP - false positive results;

FN - false negative results.

Numerical experiments have shown that neural network accuracy metrics depend on the specific network architecture (model). These experiments made it possible to identify the most effective network models in terms of accuracy. Based on a comparison of the accuracy of the model series we examined, the three most effective models were selected:

- series $2 \times 32c, N \times 64c, 128$;
- series $2 \times 64c, N \times 32, 128$;
- series $2 \times 32c, 2 \times 64c, N \times 128c, 128$.

Figure 7 shows the dependence of identification accuracy metrics for thermokarst features in the test subset on the number of layers in the $2 \times 32c, N \times 64c, 128$ model series.

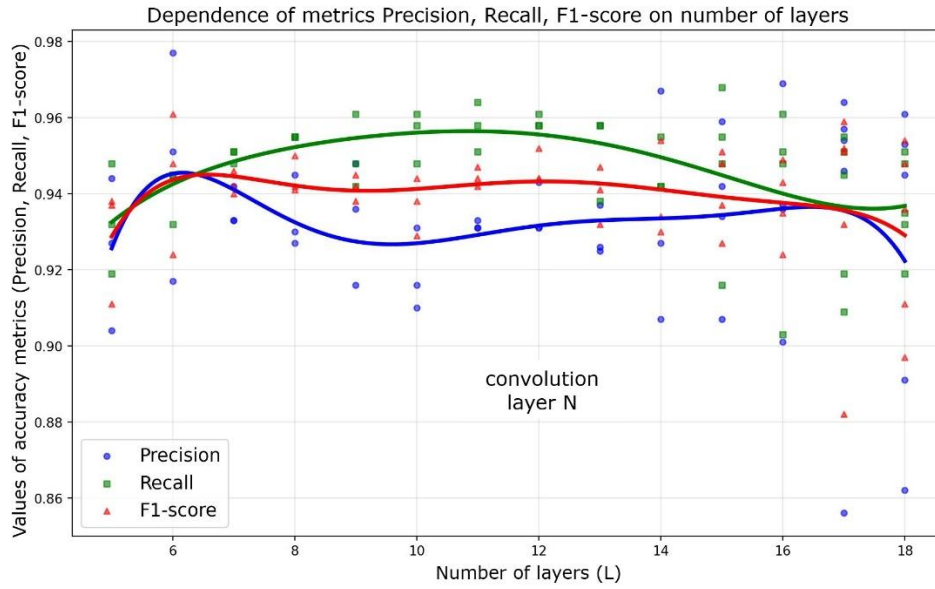


Fig. 8. Dependence of identification accuracy metrics for thermokarst features in the prediction dataset on the number of layers in the $2 \times 32c, N \times 64c, 128$ model series.

As shown in Fig. 8, the maximum identification accuracy in terms of Recall—ranging from 0.95 to 0.96 for the test subset of this series—is observed for the $2 \times 32c$, $(7-9) \times 64c$, 128 models, which consist of 10–12 layers. Regarding Precision and F1-score, the maximum values of approximately 0.95 occur when L is in the range of 6–7. A similar relationship for the $2 \times 64c$, $N \times 32$, 128 model series is presented in Fig. 9.

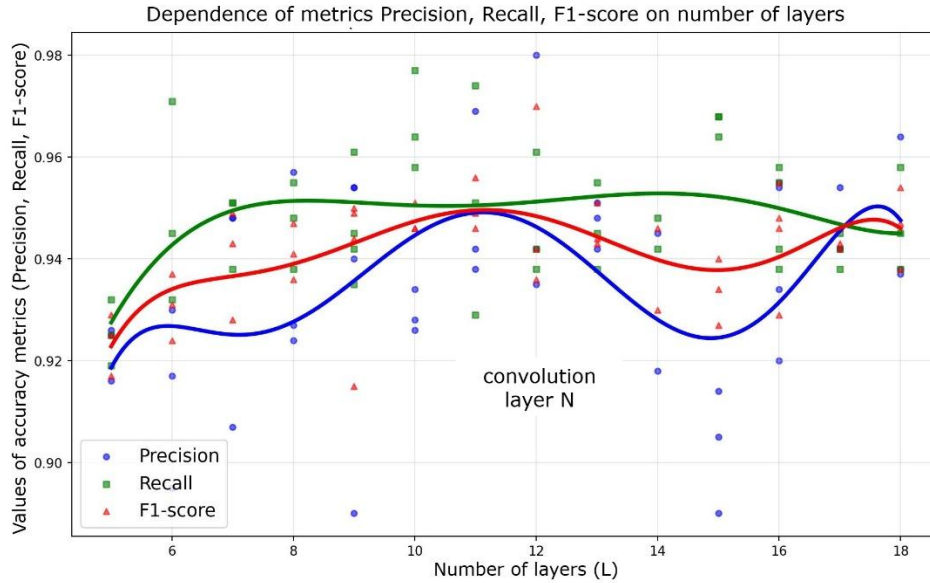


Fig. 9. Dependence of the identification accuracy of thermokarst features in the prediction set on the number of layers in the $2 \times 64c, N \times 32, 128$ model series.

Figure 9 shows that for the $2 \times 64c, N \times 32c, 128$ series, models with 14 and 15 layers exhibit maximum accuracy in terms of Recall—averaging approximately 0.95—whereas for Precision and F1-score, two maxima are observed: one at $L = 11$ and another in the 17–18 range.

Figure 10 shows the dependence of thermokarst formation identification accuracy metrics for the test subset on the number of layers for the model series $2 \times 32c, 2 \times 64c, N \times 128c$, and 128.

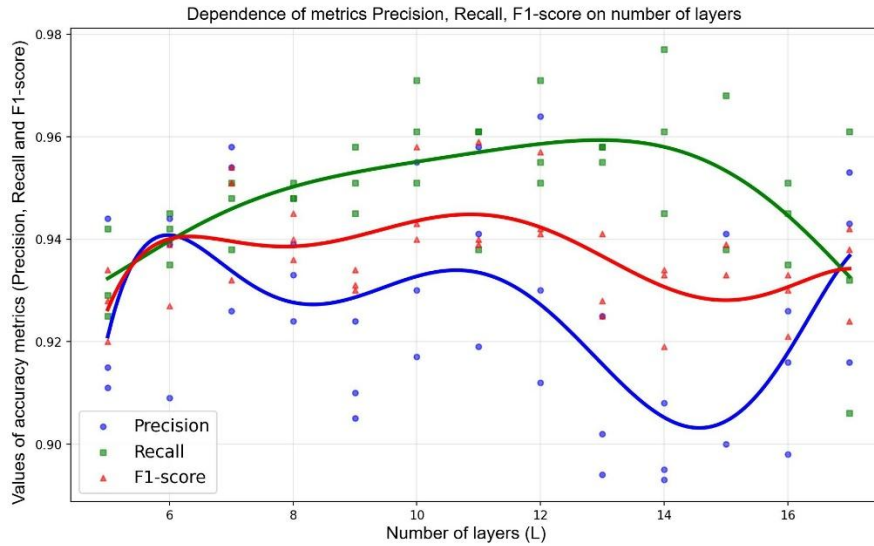


Fig. 10. Dependence of the identification accuracy of thermokarst features in the prediction set on the number of layers in the model series $2 \times 32c, 2 \times 64c, N \times 128c, 128$.

Figure 10 shows that for the $2 \times 32c, 2 \times 64c, N \times 128, 128$ series, the maximum Recall averages approximately 0.96 and occurs with 13 layers—specifically, for the $2 \times 32c, 2 \times 64c, 8 \times 128c, 128$ model. In terms of Precision and F1-score, the model with 6 layers demonstrates the highest accuracy. Thus, among the three model series mentioned above, the highest identification performance is observed for the $2 \times 32c, N \times 64c, 128$ and $2 \times 32c, 2 \times 64c, N \times 128c, 128$ series, with average Recall values of approximately 0.96. In the first case, maximum accuracy is achieved with 10–12 layers, while in the second, it occurs at 13 layers.

One of the metrics used to evaluate the quality of a neural network in classification tasks is the confusion matrix. Figures 11 and 12 show the confusion matrices for the $2 \times 32c, 3 \times 64c, 128$ and $2 \times 32c, 2 \times 64c, 6 \times 128c, 128$ models, respectively. The presented confusion matrices indicate that the network is most prone to errors when distinguishing between thermokarst features and fields.

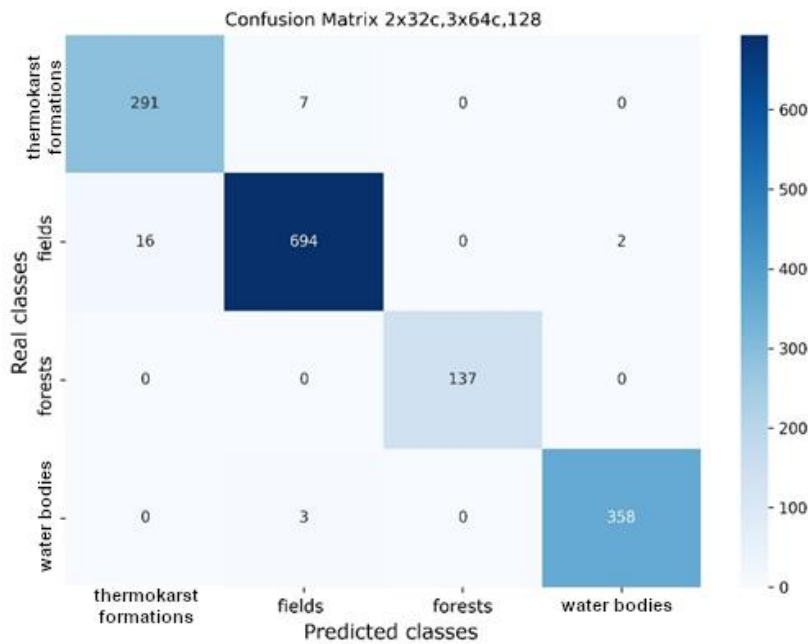


Fig. 11. Confusion matrix for the $2 \times 32c, 3 \times 64c, 128$ model.

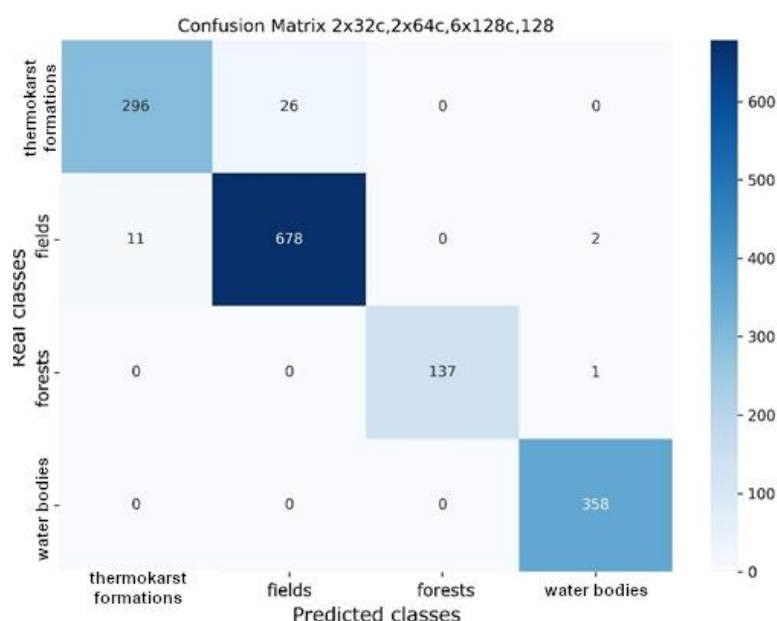


Fig. 12. Confusion matrix for the $2 \times 32c, 2 \times 64c, 6 \times 128c, 128$ model.

5 Conclusion

Research has demonstrated that a convolutional neural network can effectively recognize thermokarst landscape features in satellite imagery of central Yakutia, achieving high accuracy metrics. Based on an analysis of preliminary numerical experiments, three series of multilayer convolutional neural network models were selected ($2 \times 32c, N \times 64c, 128$; $2 \times 64c, N \times 32c, 128$; $2 \times 32c, 2 \times 64c, N \times 128c, 128$). These models demonstrate high accuracy measured by Recall, Precision, and F1-score in identifying thermokarst features within the test subset. For the first series, maximum Recall values reach 0.95–0.96, while maximum Precision and F1-score values are approximately 0.94 and 0.95, respectively. For the second series, maximum accuracy metrics (Recall, Precision, and F1-score) are around 0.9. For the third series, maximum Recall, Precision, and F1-score values are 0.96, 0.94, and 0.943, respectively. Numerical experiments revealed that the networks make the most errors when distinguishing between thermokarst formations and fields, a pattern that reflects the actual geographical distribution of thermokarst formations. The method presented in this study for identifying satellite images of early-stage thermokarst features, along with the developed application software, can be used for the automated monitoring of cryolithozone landscapes, provided that appropriate training datasets are prepared and verified.

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Contributions

V.V. – conceptualization, investigation, writing-original draft, editing; A.Yu. – visualization, resources, writing-review, editing; A.F. – validation, writing-review; B.N. – validation, writing-review.

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Ethics declarations

Competing interests

The authors declare no competing interests.

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