Identification of plankton populations in the surface waters of the Azov Sea based on neural network structures of various architectures

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Abstract. In recent years, deep learning technology has been widely used to solve the problem of recognizing the boundaries of structures on the surface of a reservoir. This technology opens up significant opportunities for the use of aerospace methods of geoecological forecasting. The purpose of this work is to identify plankton populations on the surface of the Sea of Azov, using remote sensing data, including space images of the Earth. Machine learning algorithms for segmentation of these structures on the surface of the reservoir, based on convolutional neural networks with the following architectures, are built: U-Net, FCN32, SegNet, DelitedSegNet, U-Net (transposed convolutional). A comparison of the used neural network models based on the IoU (Intersection over Union) metric is carried out. The highest accuracy was demonstrated by the algorithm created on the basis of the U-Net neural network architecture. The results obtained can be used to create maps of the distribution of plankton populations and assess water quality.

1 Introduction

Phytoplankton biomass is a key element of water body ecosystems. Development of methods that provide real-time information on the dynamics of phytoplankton populations will be useful for water resources management and optimization of the ecological component [1-4]. This will allow making informed decisions based on up-to-date data on the state of phytoplankton and water quality. Thanks to the timely information received, it is possible to optimize the processes of water body monitoring, including resource management and planning of environmental protection measures. In addition, this can also play an important role in attracting investment and financing projects related to the conservation of water body ecosystems. Earth remote sensing (ERS) technology offers effective ways of continuous monitoring of phytoplankton biomass at various scales. ERS data sets allow obtaining spatio-temporal correlation of images, which can be appropriately used to map the boundaries of these structures on the water surface. Artificial intelligence technologies contribute to the improvement and automation of procedures for interpreting and analyzing data obtained from remote sensing using spacecraft [5-8]. Algorithms based on deep learning are capable of processing huge amounts of data in a matter of minutes. One of the advantages of using

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algorithms based on deep learning to process remote sensing data is the high speed of information processing, which significantly accelerates decision making. Russia has accumulated significant experience in this area. Here I would like to note the work carried out at the P.P. Shirshov Institute of Oceanology of the Russian Academy of Sciences, the St. Petersburg State Marine Technical University, and the Southern Federal University [9–14].

Algorithms for analyzing and processing halftone images – spots of plankton populations – are being developed at the Don State Technical University using remote sensing data to determine the coordinates of their boundaries and intensities (concentrations) based on a combination of local binary template (LBP) methods and neural systems [15-17].

Despite the existing groundwork, issues of processing remote sensing data, as applied to studies related to the recognition of plankton populations in marine waters, require additional developments. In the context of the problem under consideration, extracting information about phytoplankton populations from remote sensing data is the main goal of image analysis using computer vision methods. This work devoted to these studies.

2 Materials and Methods

In this study, a set of space images of the Roscosmos State Corporation (freely available images, 2019-2021) for the surface of the Sea of Azov was used. In each image, areas of plankton populations were manually marked. To obtain a more diverse dataset, we resort to image augmentation. The augmentation operations performed include vertical and horizontal flips, clockwise and counterclockwise rotations.

In the work, the following neural network architectures were used: FCN32 (Table 2), SegNet (Table 3), DelitedSegNet, UNet (Table 4), UNet + transposed convolutional. The VGG16 architecture (Table 1) was chosen as part of the classifier for FCN32. Each of the architectures was adapted for images with a resolution of 224×224×3.

Table 1. VGG16 architecture used as classifier in FCN32 with input image 224×224×3.

Layer name	Layers and the number of their repetitions	Number of feature maps	Convolution kernel size	Output image size
Conv1	Conv + ReLU, 2	64	3× 3	224×224×64
Pool1	Maxpool	-	2×2	112×112×64
Conv2	Conv + ReLU, 2	128	3× 3	112×112×128
Pool2	Maxpool	-	2×2	56×56×128
Conv3	Conv + ReLU, 2	256	3× 3	56×56×256
Pool3	Maxpool	-	2×2	28×28×256
Conv4	Conv + ReLU, 3	512	3× 3	28×28×512
Pool4	Maxpool	-	2×2	14×14×512
Conv5	Conv + ReLU, 3	512	3× 3	14×14×512
Pool5	Maxpool	-	2×2	7×7×512

Table 2. architecture FCN32 with input image 224×224×3.

Layer name	Layers and the number of their repetitions	Number of feature maps	Convolution kernel size	Output image size
Encoder	VGG16	-	-	7×7×512

Upsample1	Transposed Conv + ReLU	512	3×3	14×14×512
Upsample2	Transposed Conv + ReLU	256	3×3	28×28×256
Upsample3	Transposed Conv + ReLU	128	3×3	56×56×128
Upsample4	Transposed Conv + ReLU	64	3×3	112×112×64
Upsample5	Transposed Conv + ReLU	32	3×3	224×224×32
Conv1	Conv	2	1×1	224×224×2

Table 3. architecture SegNet, with input image 224×224×3.

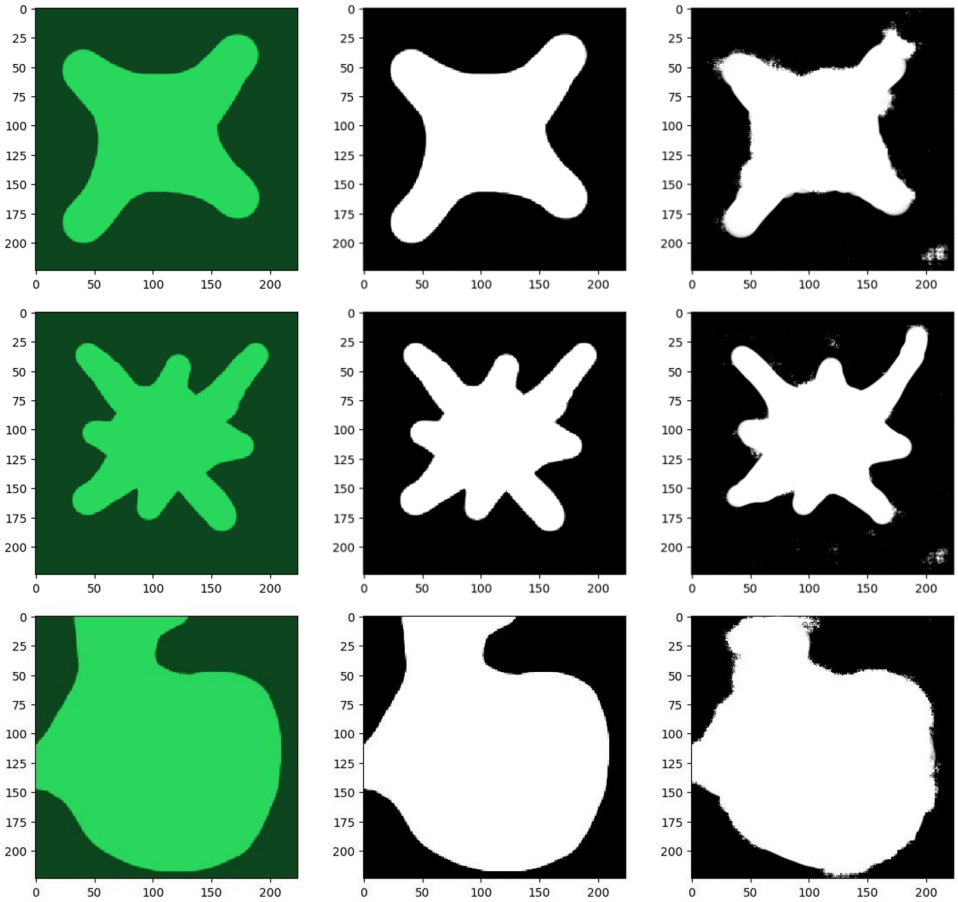
Layer name	Layers and the number of their repetitions	Number of feature maps	Convolution kernel size	Output image size
Conv1	Conv + BatchNorm + ReLU, 2	64	3×3	224×224×64
Pool1	Maxpool	-	2×2	112×112×64
Conv2	Conv + BatchNorm + ReLU, 2	128	3×3	112×112×128
Pool2	Maxpool	-	2×2	56×56×128
Conv3	Conv + BatchNorm + ReLU, 3	256	3×3	56×56×256
Pool3	Maxpool	-	2×2	28×28×256
Conv4	Conv + BatchNorm + ReLU, 3	512	3×3	28×28×512
Pool4	Maxpool	-	2×2	14×14×512
Bottleneck	Conv + ReLU, 2	256	3×3	14×14×256
Upsample1	Upsample	-	2×2	28×28×256
Conv5	Conv + BatchNorm + ReLU, 3	128	3×3	28×28×128
Upsample2	Upsample	-	2×2	56×56×128
Conv6	Conv + BatchNorm + ReLU, 3	64	3×3	56×56×64
Upsample3	Upsample	-	2×2	112×112×64
Conv7	Conv + BatchNorm + ReLU, 2	32	3×3	112×112×32
Upsample4	Upsample	-	2×2	224×224×32
Conv8	Conv + BatchNorm + ReLU, 2	2	3×3	224×224×2

Table 4. architecture UNet, with input image 224×224×3.

Layer name	Layers and the number of their repetitions	Number of feature maps	Convolution kernel size	Output image size
Conv1	Conv + BatchNorm + ReLU, 2	32	3×3	224×224×32
Pool1	Maxpool	-	2×2	112×112×32
Conv2	Conv + BatchNorm + ReLU, 2	64	3×3	112×112×64
Pool2	Maxpool	-	2×2	56×56×64
Conv3	Conv + BatchNorm + ReLU, 3	128	3×3	56×56×128
Pool3	Maxpool	-	2×2	28×28×128
Conv4	Conv + BatchNorm + ReLU, 3	256	3×3	28×28×512
Pool4	Maxpool	-	2×2	14×14×512
Bottleneck	Conv + ReLU, 2	256	3×3	14×14×256
Upsample1	Upsample	-	2×2	28×28×256
Concatenate1	Concatenate	-	-	28×28×512
Conv5	Conv + BatchNorm + ReLU, 3	128	3×3	28×28×128
Upsample2	Upsample	-	2×2	56×56×128
Concatenate2	Concatenate	-	-	56×56×256
Conv6	Conv + BatchNorm + ReLU, 3	64	3×3	56×56×64
Upsample3	Upsample	-	2×2	112×112×64
Concatenate3	Concatenate	-	-	112×112×128
Conv7	Conv + BatchNorm + ReLU, 2	32	3×3	112×112×32
Upsample4	Upsample	-	2×2	224×224×32
Concatenate4	Concatenate	-	-	224×224×64
Conv8	Conv + BatchNorm + ReLU, 2	2	3×3	224×224×2

3 Results

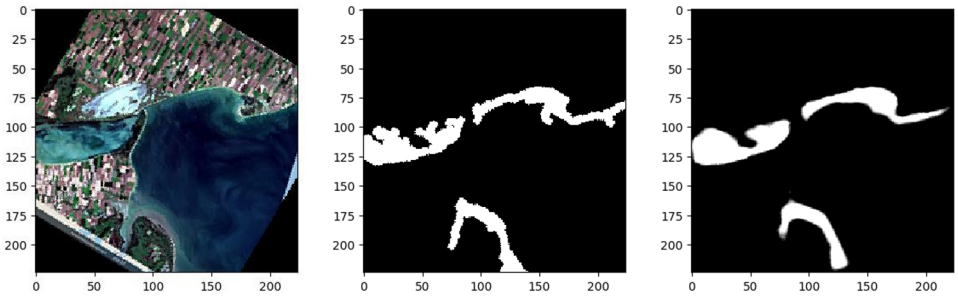
Before training, the training and test data were split in a ratio of 9 to 1. The UNet model was trained using the Adam optimizer with the following hyperparameters: learning rate – 0.001, $\beta_1 = 0.9, \beta_2 = 0.99$. The result of numerical experiments conducted for the training domains is presented in Fig. 1.

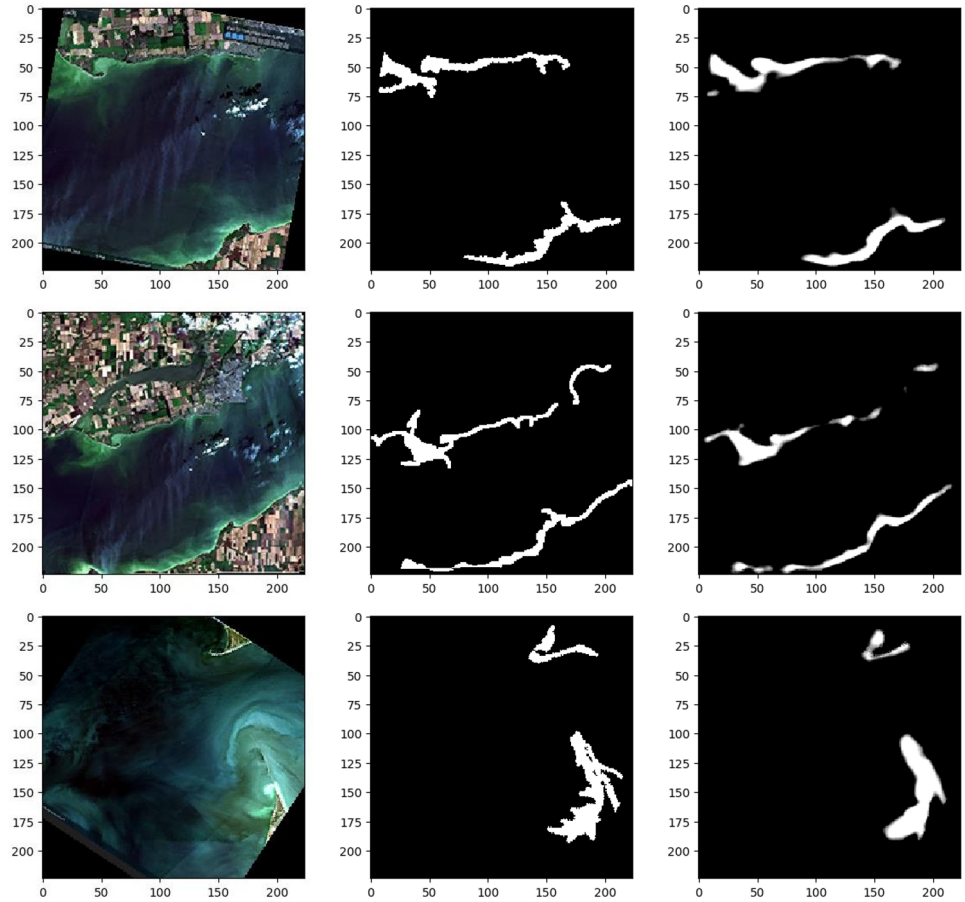


a) input images *b*) image masks *c*) segmentation results

Fig. 1. Numerical experiments performed for training domains.

Further, satellite images of areas of the Sea of Azov from 2019 to 2021, which were freely available on the Roscosmos geoportal, were used as initial data (Fig. 2).





a) input images *b*) image masks *c*) segmentation results

Fig. 2. Results of applying the UNet model to test images.

4 Discussion

To evaluate the metric of automated classifiers, the IoU metric (intersection over union metric) was used, which has become widely used in detection and segmentation problems:

$$IoU=|A\cap B|/(|A|\cup|B|), \quad (1)$$

where $|A\cap B|$ is the area in pixels of overlap between the area proposed by the computer (A) and the true image (B); $|A|\cup|B|$ is the total number of pixels contained in both areas.

Table 5. Comparison of the results of the conducted research.

The neural network model used for recognition	Recognition probability determined by the IoU metric on training images	Recognition probability determined by the IoU metric on satellite images
UNet	**83%**	**68%**

SegNet	79%	53%
UNet (conv transposed)	82%	64%
DelitedSegNet	80%	57%
FCN32	75%	47%

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References

1. A. Sukhinov, Y. Belova, A. Nikitina, V. Sidoryakina, Mathematics **10**(12), 2092, (2022). DOI: 10.3390/math10122092.
2. A.I. Sukhinov, A.A. Sukhinov, V.V. Sidoryakina, IOP Conf. Series: Journal of Physics: Conference Series **1479**(1), 012081 (2020). DOI 10.1088/1742-6596/1479/1/012081.
3. V.V. Sidoryakina, *Efficient algorithms for the numerical solution of the coupled sediment and suspended matter transport problems in coastal systems*. Proceedings of the 21st International Workshop on Computer Science and Information Technologies (CSIT 2019) Series: Atlantis Highlights in Computer Sciences, vol. 3, pp. 243-248 (2019). DOI: 10.2991/csit-19.2019.42.
4. A.I. Sukhinov, A.E. Chistyakov, V.V. Sidoryakina, S.V. Protsenko, A.M. Atayan, Mathematical Physics and Computer Simulation **24**(2), 38-53 (2021). DOI: 10.15688/mpcm.jvolsu.2021.2.4.
5. K.M. Abdullina, A.I. Spivak, Scientific and Technical Journal of Information Technologies, Mechanics and Optics **20**(3), 425-431 (2020). DOI: 10.17586/2226-1494-2020-20-3-425-431.
6. O. Ronneberger, Ph. Fischer, Th. Brox, arXiv:1505.04597 [cs.CV] (2021). DOI: 10.48550/arXiv.1505.04597.
7. V. Badrinarayanan, A. Kendall, R. Cipolla, arXiv:1511.00561 [cs.CV] (2015). DOI: 10.48550/arXiv.1511.00561.
8. E. Shelhamer, J. Long, T. Darrell, IEEE Transactions on Pattern Analysis and Machine Intelligence **39**(4), 640-651 (2016). DOI: 10.1109/TPAMI.2016.2572683.
9. O.V. Kopelevich, S.V. Vazyulya, I.V. Saling, S.V. Sheberstov, V.I. Burenko, Modern problems of remote sensing of the Earth from space **12**(6), 99–110 (2015).
10. A.V. Bocharov, O.A. Tikhomirov, S.D. Khizhnyak, P.M. Pakhomov, Journal of Applied Spectroscopy **84**(2), 291-295 (2017). DOI: 10.1007/s10812-017-0466-7.
11. O.A. Tikhomirov, A.V. Bocharov, A.B. Komissarov, S.D. Khizhnyak, P.M. Pakhomov, Bulletin of Tver State University. Series: Chemistry **2**, 230-244 (2016).
12. D. Krivoguz, L. Bespalova, A. Zhilenkov, S. Chernyi, J. Mar. Sci. Eng **10**, 1392 (2022). DOI: 10.3390/jmse10101392.
13. D. Krivoguz, S.G. Chernyi, E. Zinchenko, A. Silkin, A. Zinchenko, Data **8**(9), 138 (2023). DOI: 10.3390/data8090138.
14. D. Krivoguz, E. Bespalova, A. Zhilenkov, S. Chernyi, A. Kustov, A. Degtyarev, E. Zinchenko, Climate **12**, 120 (2024). DOI: 10.3390/cli12080120.

15. N.D. Panasenko, Computational Mathematics and Information Technologies **7**(4), 54-65 (2023). DOI: 10.23947/2587-8999-2023-7-4-54-65.
16. A.I. Sukhinov, S.V. Protsenko, N.D. Panasenko, Computational Mathematics and Information Technologies **6**(3), 104–113 (2022). DOI: 10.23947/2587-8999-2022-1-3-104-113.
17. A. Sukhinov, N. Panasenko, A. Simorin, Algorithms and programs based on neural networks and local binary patterns approaches for monitoring plankton populations in sea systems. E3S Web of Conferences 363, 02027 (2022). DOI: 10.1051/e3sconf/202236302027.