Scientific Visualization, 2025, volume 17, number 4, pages 30 - 38, DOI: 10.26583/sv.17.4.04

This paper is an extended version of a contribution presented
at the Graphicon 2025 conference.

The Contours Visualization in Satellite Image of Natural Objects by Artificial Intelligence

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Abstract

The paper discusses machine learning methods for satellite image classification. We present a neural network algorithm for visualization of the shapes of natural objects, using a variety of machine learning algorithms for preprocessing the training dataset. Our paper compares the classification of the algorithm, calculates its accuracy, and proposes potential improvements. We tested our approach on satellite images of woodland areas in the Bolsheboldinsky District in Russia. The results demonstrate that our improved neural network algorithm achieves high computational accuracy. Robustness, recall, and overall accuracy reach 0.98, especially using training datasets optimized with a support vector machine (SVM). We also demonstrated the applicability of our method for creating accurate geographic information models and detecting changes in natural resources.

Keywords: geometric modeling, geoinformation modeling, neural network, natural resources, visualization of object boundaries, image classification.

1. Introduction

Satellite images are now one of the most frequently used materials for studying natural objects. Analysts analyze satellite images to recognize natural or man-made objects and use the resulting data for analytics and forecasting. Artificial intelligence technologies based on machine learning and computer vision methods typically serve as tools in this research.

Combining artificial intelligence capabilities with geoinformation technologies solves several important interrelated tasks. First, it visualizes the contours of studied objects on a satellite image. Second, during regular observations, it accumulates material for analytics and forecasting possible changes in the contours and areas of target objects using only a computer workstation. Thus, one can observe changes in the contours of target objects over a certain period and, after accumulating sufficient data, forecast the further territory development. A high-quality forecast is crucial for decision-making in managing both specific resources and the entire study area.

In the last decade, many Russian and foreign scientists have dedicated research to exploring artificial intelligence capabilities for recognizing natural and anthropogenic objects on satellite images, visually highlighting their contours and occupied areas. Some focus on highly reliable recognition and visualization of studied objects and their automated categorization and typification. Researchers typically combine applied machine learning methods, often using a neural network as the primary combination method. For example, [1] describes using the U-Net deep learning neural network combined with the ES-Net semantic neural network to study forest conditions; [2] considers using time series and a multiscale geographically weighted regression (MGWR) model, where the Random Forest method recognizes data from satellite images in crop research. Other studies focus on forecasting situation development regarding changes in the contours of studied objects. The main subjects of study are natural objects – forests, agricultural lands and cultivated plantations, watercourses and reservoirs, coastal zones of rivers, seas, and oceans. For instance, study [3] focuses on forecasting crop development, particularly wheat, using five different machine learning algorithms (Random Forest, Gradient Boosting, AdaBoost, LightGBM, and XGBoost); concluding on their performance, it considers the XGBoost model the most successful. Furthermore, using data from multiple sources combined with machine learning algorithms increases forecasting accuracy and adds new capabilities to agricultural decision support systems. A similar conclusion appears in study [4], which applies small area estimation methods and statistical regression methods combined with data from open sources – the Landsat 8 satellite and the Google Earth Engine platform – for researching forest quality. Work [5] describes the Segment Anything Model (SAM), which performs image segmentation. This article shows how researchers can adapt such foundation models for Earth remote sensing tasks. The authors of [6] focus on solving the problem of precise boundary extraction in remote sensing images by using contextual information.

For the presented research, we selected natural objects located in the *Bolsheboldinsky District* of the *Nizhny Novgorod Region*, which hold substantial value for this territory – forest areas. The significance of these natural objects and the applied methods make the research relevant and in demand.

2. Problem Statement

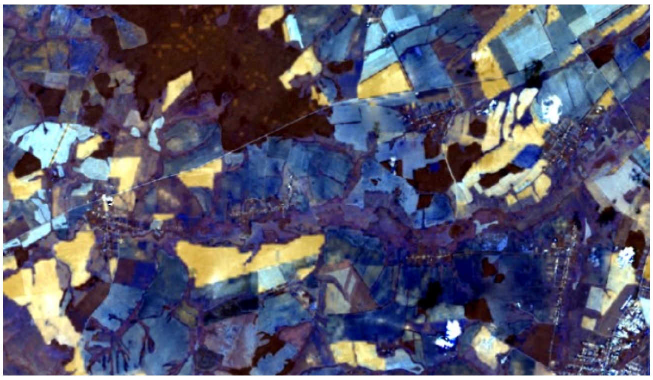
Experts widely use remote sensing data to study objects occupying large areas on the Earth's surface. Forest areas undoubtedly belong to such objects [7]. Most often, researchers obtain this data from satellite imagery, aerial photography, and images from unmanned aerial vehicles. Since the latter two sources require specific tools and are not always freely accessible, we decided to use satellite image repository materials available to a wide range of users. From existing open sources, we selected images of the study area from 2014 to 2024, taken by Landsat 8 and 9 satellites during the vegetation period (May to September) in good, clear, and cloudless weather, as such images required fewer preliminary processing procedures. We could use these images to create a geoinformation model visualizing the contours of studied objects on a raster image.

Processing remote sensing data of the earth's surface from satellite images in geoinformation systems allows specialists to work with all the region's natural resources or focus on individual, most important objects. This work required a sufficiently efficient and relatively simple algorithm for recognizing images of the studied natural objects on satellite images, visualizing their contours, and using the results for further solutions.

3. Theory

3.1. Features of the Studied Objects

Forest areas belong to the category of objects lacking typical contours, which visual analysis of the selected satellite image fragments confirms (Fig.1). This complicates recognizing and visualizing their contours on satellite images using the recently widespread convolutional neural networks (CNNs). We believe that using a classic "supervised" neural network algorithm, which includes the error backpropagation method, is more acceptable for recognizing forest area images. They also considered the requirement for resource economy during algorithm development and implementation.



(a)

(b)

Fig. 1. Fragments of vector layers of an image with forest areas: (a) -- fragment 1; (b) -- fragment 2

3.2. Work Main Stages on Visualizing Forest Areas

The following stages of working with the selected images within the considered approach involved applying geoinformation technologies and took place in the QGIS geoinformation system:

– Assembling a raster image using the GDAL Tools module;
– Selecting image scenes containing the study area;
– Separating scene fragments containing forest areas;
– Modeling forest areas using QGIS plugins [6];
– Obtaining a labeled single-channel raster with images of forest areas.

During image assembly, we took data from channels 1 to 7 and combined them in the GDAL Tools QGIS virtual environment. Then, on the selected image fragments containing forest areas, we added vector layers for labeling and classifying forest area images using reference polygons.

Within this research, visualizing forest area images means performing a dichotomous classification of the selected satellite image scene fragment, which produced single-channel rasters with two-pixel types – belonging to forest areas and not belonging to them. The primary research method – a neural network algorithm – performed this classification. We prepared training datasets for it using four well-known machine learning algorithms – Gaussian Mixture Model, Random Forest, Support Vector Machines, K-Nearest Neighbors, implemented in QGIS via built-in plugins [8]. After preparing the datasets and training the neural network, we performed recognition and visualization of forest area contours on the selected satellite image fragments. The visualization results of forest areas by the neural network algorithm are shown for fragment 1 (Fig. 2) and fragment 2 (Fig. 3) with training sets prepared by each mentioned method.

Note that in previous stages of the research described in [9], the neural network algorithm used 14 input nodes and two activation functions, ReLu and Softmax, as it needed to implement dichotomous classification. We implemented the network in the Python programming language, using functions from the Numpy, PirsGis, and TensorFlow libraries. However, when trying to implement the algorithm in the open QGIS geoinformation system, we discovered that not all QGIS versions could run it correctly. Therefore, they modified the algorithm to eliminate these problems as follows: to increase accuracy, they used 64 nodes and the same activation functions, serving the Python libraries numpy, pirsgis, scikit-learn. This modification should allow its future use as a plugin for the open-source GIS QGIS, expanding its application possibilities and potentially representing certain novelty in the conducted research.

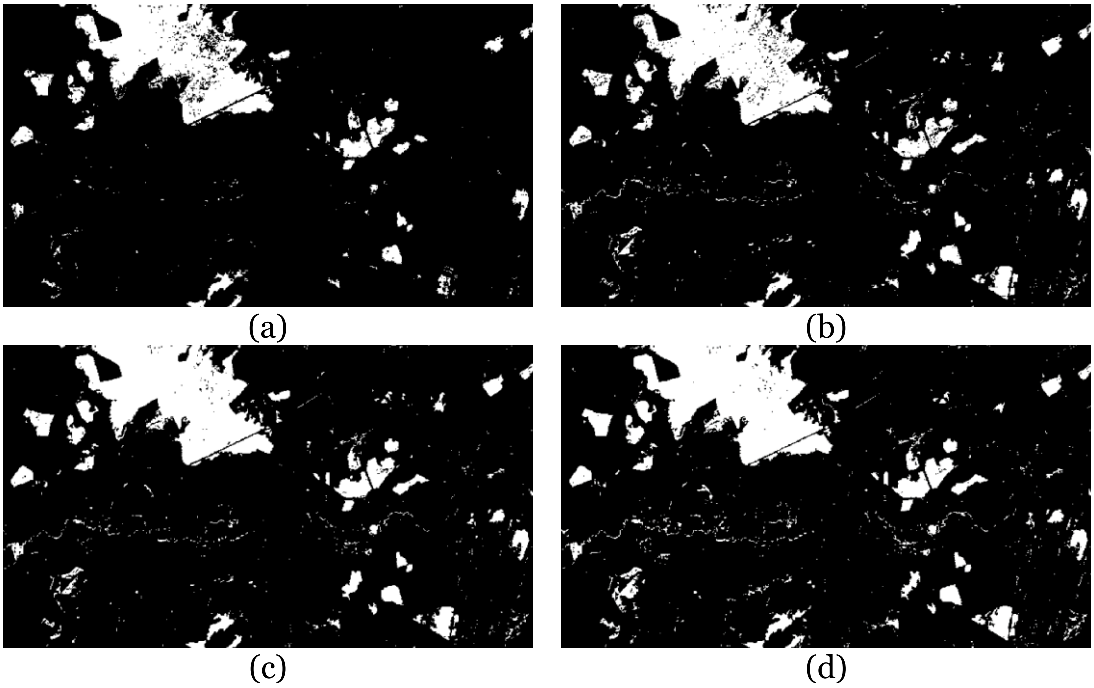


Fig. 2. Visualization of forest areas on fragment 1 with training sets prepared by methods: (a) -- Gaussian Mixture Model; (b) -- K-Nearest Neighbors; (c) - Random Forest; (d) - Support Vector Machines

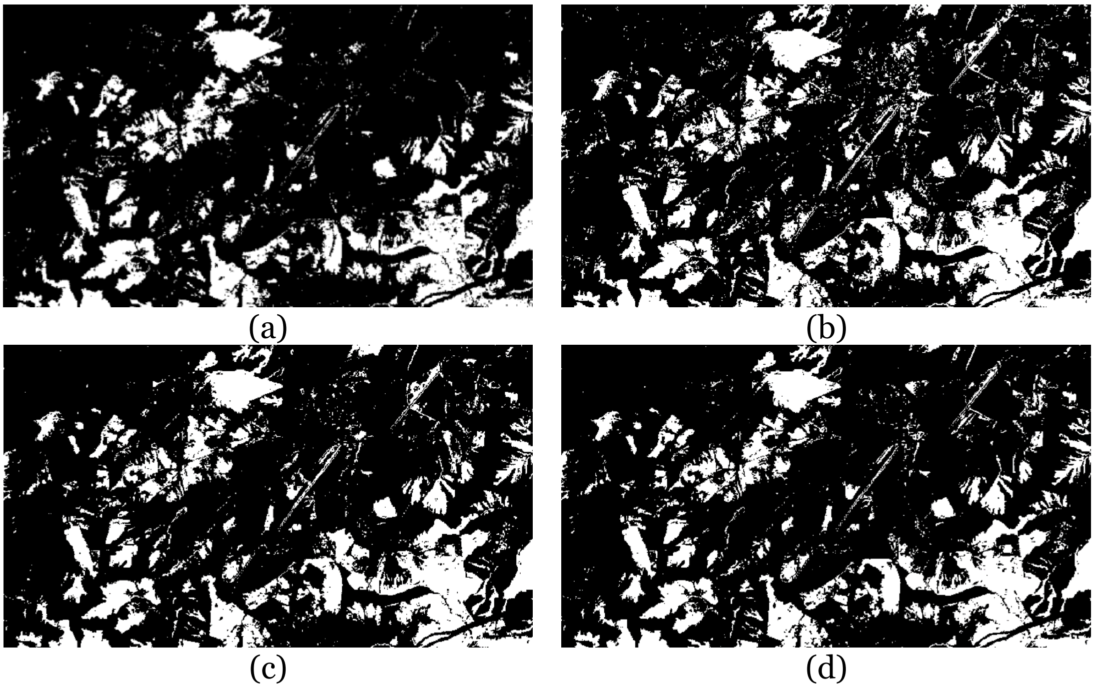


Fig. 3. Visualization of forest areas on fragment 2 with training sets prepared by methods: (a) -- Gaussian Mixture Model; (b) -- K-Nearest Neighbors; (c) -- Random Forest; (d) - Support Vector Machines

4. Tests

After training using datasets prepared with the mentioned machine learning methods, the neural network showed generally acceptable results in the confusion matrix and corresponding metrics – robustness, recall, and overall accuracy. This allows considering the predicted visualization values satisfactory and indicative of achieving the set goals.

Table 1 presents the confusion matrix data for visualizing forest area images on fragment 1; Table 2 shows data for fragment 2. The table data indicates that the fragment with a larger number of forest areas recognizes as effectively and reliably as the fragment with fewer forest areas, suggesting the algorithm independence from the number of pixels of recognizable objects.

Table 1. Confusion Matrix Data for Fragment 1

Training Set	TN	FN	FP	TP
GMM	17657	115	299	5629
KNN	17747	427	104	5422
RendF	17371	122	516	5691
SVM	17243	268	263	5926

Table 2. Confusion Matrix Data for Fragment 2

Training Set	TN	FN	FP	TP
GMM	17276	33	680	5711
KNN	17567	180	180	5669
RendF	17792	523	95	5290
SVM	17264	268	242	5926

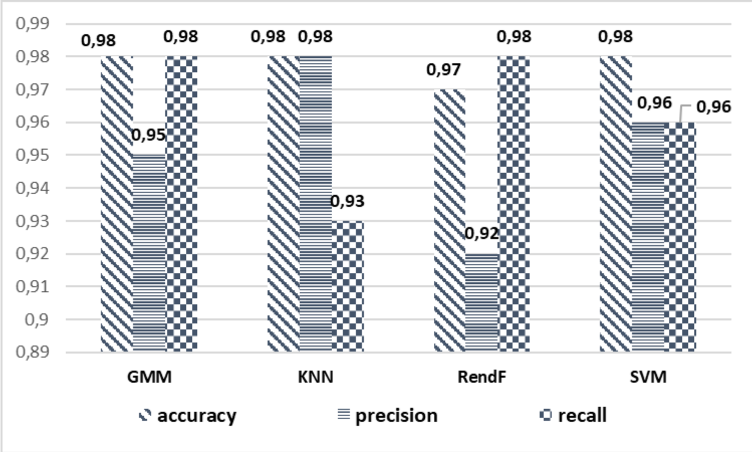
5. Discussion

Metrics calculated on the basis of confusion matrix show sufficient accuracy and success of the neural network algorithm with each prepared dataset (see tables 1-2). However, one can discuss more or less successful algorithm runs with some training sets and identify the set that is most stable with the developed neural network algorithm. As Fig. 4 shows, the algorithm is most stable with the training dataset prepared using the Support Vector Machines (SVM) method.

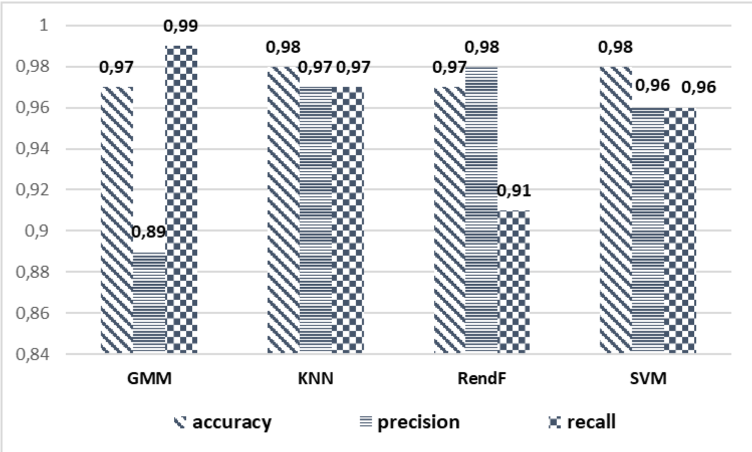
The neural network metrics are higher compared to those described in [7], ranging within: accuracy 0.97-0.98, precision 0.91-0.98, recall 0.93-0.98.

Since we obtained positive experience with training datasets for the neural network by machine learning methods that inherently introduce certain deviations, we further continued the series of experiments with the neural network algorithm. For this, a raster obtained through precise interpretation using the Google Earth Explorer base layer was used as the second component of the training dataset.

Finally, we got a single-channel raster. This, paired with a multi-channel raster of similar dimensions for the selected territory, constitutes the training dataset for the neural network algorithm (Fig. 5).



(a)



(b)

Fig. 4. Visualization of neural network algorithm metric values: (a) -- fragment 1; (b) -- fragment 2

Fig. 5. Training dataset prepared through precise interpretation

Subsequent work focused on selecting optimal values for the neural network parameters: the number of training epochs and the number of tests during training to determine the minimum standard deviation value.

As follows from the test analysis the algorithm with the number of training epochs set to 14 and 2 consecutive experiments during the training configuration (Table 3) demonstrated the most stable performance. This configuration also shows the most reliable prediction result when compared with reference values (Fig. 6).

Table 3. Neural Network parameter definition

Training Epochs	Training tests	precision	recall	accuracy
12	2	0,979	0,991	0,97555
12	3	0,978	0,992	0,97610
12	4	0,980	0,991	0,97064
12	6	0,974	0,994	0,97608
14	2	0,974	0,994	0,97517
14	2	0,977	0,992	0,97681
14	2	0,969	0,996	0,97327
14	4	0,983	0,987	0,97712
14	4	0,980	0,991	0,97759

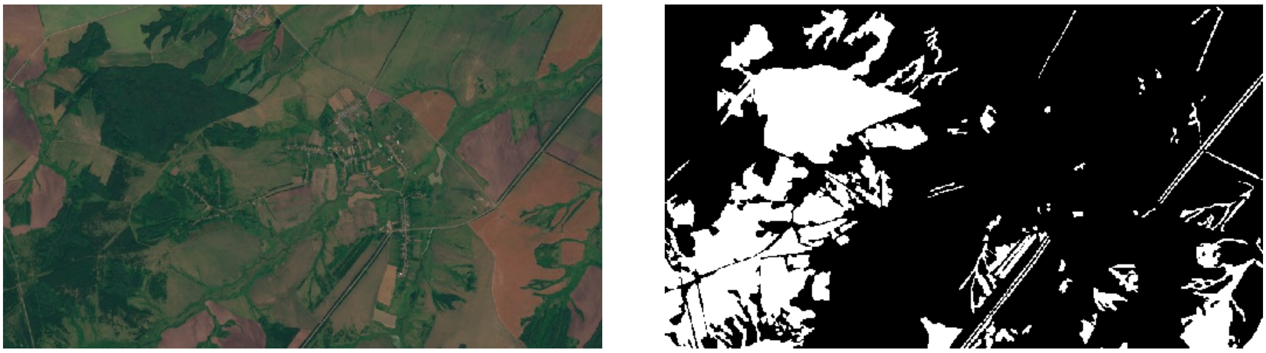


Fig. 6. A photo fragment and the output after processing it with a neural network

Analysis of the obtained results clearly showed that the developed algorithm extracts contours of plane geometric shapes with complex, irregular structures at an accuracy acceptable for subsequent research stages. Thus, the standard training metrics of the neural network algorithm with the final selected parameter values had the following stable indicators: precision - 0.97, recall - 0.99, accuracy - 0.98. The standard deviation varied in the range from 0.0001 to 0.0008.

6. Conclusion

At this research stage, the authors conclude that automated methods for recognizing objects on satellite images require more thorough preparation of initial data. Specifically, machine learning algorithms can prepare the training dataset. This approach will yield a more accurate geoinformation model of the study area, visualizing the contours and areas of the studied objects. The modified neural network algorithm, with an increased number of nodes and optimized library usage, showed stable and high performance, particularly with the SVM-prepared training set. This success paves the way for integrating the algorithm as a plugin into the open-source QGIS, enhancing its accessibility for a broader range of specialists. The main focus of the model's improvement is extending it to other types of objects of various natures, not only in satellite but also in other images, as well as expanding the capabilities of temporal analysis to detect and predict long-term changes in objects. Several approaches in this direction hold significant interest. For instance, work [10] addresses long-term change forecasting and describes modern methods for monitoring forests using Landsat time series. Furthermore, modern Transformer architectures [11], [12] for forest mapping, which are now replacing purely convolutional networks, also show great promise.

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