APPLICATION OF ARTIFICIAL INTELLIGENCE FOR DETECTION OF LAND PLOTS

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Abstract. Significant damage to land resources as a result of military operations necessitated the introduction of modern approaches to assessing their degradation and determining the need for appropriate reclamation. The purpose of study was to develop approaches to the application of artificial intelligence technologies for operational monitoring of damaged areas and assessment of the amount of resources needed for their restoration. The processing of satellite images was carried out using computer vision algorithms based on deep learning methods, in particular YOLO convolutional neural networks implemented in the cloud infrastructure. The results of the study confirmed the high efficiency of the proposed approach. A representative sample of 9,094 satellite images of three scaling levels was formed, which provided a comprehensive analysis of degraded areas. The adaptation of the PyCDA model, originally intended for the detection of planetary craters, made it possible to achieve the accuracy of identification of land degradation signs at the level of 82%, and in conditions of minimal visual noise - up to 90%. Models based on architectures of medium complexity – YOLOv5m and YOLOv11m – demonstrated the highest performance indicators among the studied architectures, providing an optimal balance between detection accuracy and processing speed. Applying Evolve's genetically optimized augmentation strategies resulted in two-fold increase in accuracy metrics compared to baseline approaches, with even the first quartile of metric values exceeding the third quartile of standard method results. Optimization of hyperparameters provided an increase in detection accuracy by 4.6% and a decrease in number of false positives by 7%. The practical significance of the research lies in creation of a toolkit for identifying and assessing the state of degraded lands, which is an important component of their restoration strategies for use by state and environmental institutions.

Keywords: geoanalytics, computer vision, machine learning, image augmentation, land reclamation.

Introduction

Military conflicts have a significant destructive impact on the environment and land resources, which necessitates the need for prompt, automated, and accurate monitoring of damaged land using remote sensing. To address this issue, O. Dietrich et al. [1] developed an open tool platform for assessing the extent of destruction in Ukraine based on the processing of Sentinel-1 radar satellite data.

Their approach is based on time series analysis and the use of machine learning methods to determine the level of damage to buildings. The solution is implemented on the Google Earth Engine platform, which allows for monitoring with high spatial resolution in real time. In the direction of detailed analysis of structural changes on the surface, the method proposed by B. Feizizadeh et al. [2] turned out to be promising, combining object-oriented processing of satellite images with deep learning. The developed model detects spatial signs of man-made impact, in particular, explosion craters, trenches, and soil cover disturbances.

The scientific community is actively researching the application of artificial intelligence (AI) methods to the analysis of satellite images and images obtained from drones. In particular, the work [3] demonstrated the effectiveness of convolutional neural networks in the tasks of automated crater recognition on planets, which became the basis for adapting these methods to the tasks of identifying explosive craters on the Earth's surface.

The conducted studies also demonstrated the feasibility of using transfer learning, which involves adapting pre-trained models to new tasks, which significantly reduces the amount of required computing resources [4]. In addition, the work [5] presents approaches to optimizing hyperparameters of deep neural networks, which contribute to improving the accuracy of visual data analysis. The work of C. Wang et al. [6] presents the YOLOv5 architecture for detection and classification tasks. The authors [7] proposed improvements in the structure of convolutional layers and the learning strategy, which made it possible to achieve a balance between speed and accuracy even with limited computing resources [8]. This model became a platform for further adaptation to the tasks of detecting explosive damage in satellite images [9].

The aim of the article is to develop a methodology for automated analysis of degraded areas using artificial intelligence tools based on satellite images.

Materials and methods

The research was conducted based on the use of modern artificial intelligence methods for detecting damage to land plots during military operations. The implementation of the proposed approach involved a multi-stage procedure that included the collection and pre-processing of satellite images, training computer vision models, and optimization of hyperparameters.

At the initial stage, satellite images were collected using the Google Maps API. A 100 km² area liberated from occupation in the Gostomel district of the Kyiv region was selected as the study area. To form a representative sample, images of three zoom levels were used: 17 (≈192 m), 18 (≈96 m) and 19 (≈48 m). This allowed for analysis with both wide coverage of the territory and high detail of individual objects. A total of 9094 images were collected, which underwent manual labelling using the Label Studio tool.

Next, a procedure for identifying explosion craters using transfer learning based on the PyCDA model, as well as the deep learning models YOLOv5 and YOLOv11, was implemented. The PyCDA model was primarily trained to recognize craters on planetary surfaces. The adaptation involved pre-processing of images aimed at approximating their visual characteristics to those used during the initial training of the model, as well as further training of the model on satellite images of the Earth's surface obtained in the combat zone. Labelled data was used to train computer vision models based on convolutional neural networks. Finally, the influence of a number of factors on the accuracy of the models was assessed, and a strategy for data preparation and parameterization of the training process was determined, taking into account the relationship between the quality of the results and the speed of computational procedures.

Results and discussion

Within the experimental part of the study, a sample of 9094 satellite images obtained from three zoom levels: Zoom 17, Zoom 18 and Zoom 19 was formed. The Label Studio platform was used to annotate the images, which allowed creating a structured dataset for training and testing computer vision models. The basic results were obtained using the YOLOv5 and YOLOv11 architectures with typical parameters without the use of augmentation procedures, while the base model was taken as a variant trained on Zoom 17 images for 50 epochs.

The PyCDA model, originally trained for crater recognition on planetary surfaces, was adapted by preprocessing satellite images to approximate their visual characteristics to those used during the initial model training. The adaptation procedure included converting images to grayscale, applying a Gaussian filter to reduce noise, and correcting brightness and contrast using two-dimensional convolutional filtering (Fig. 1).

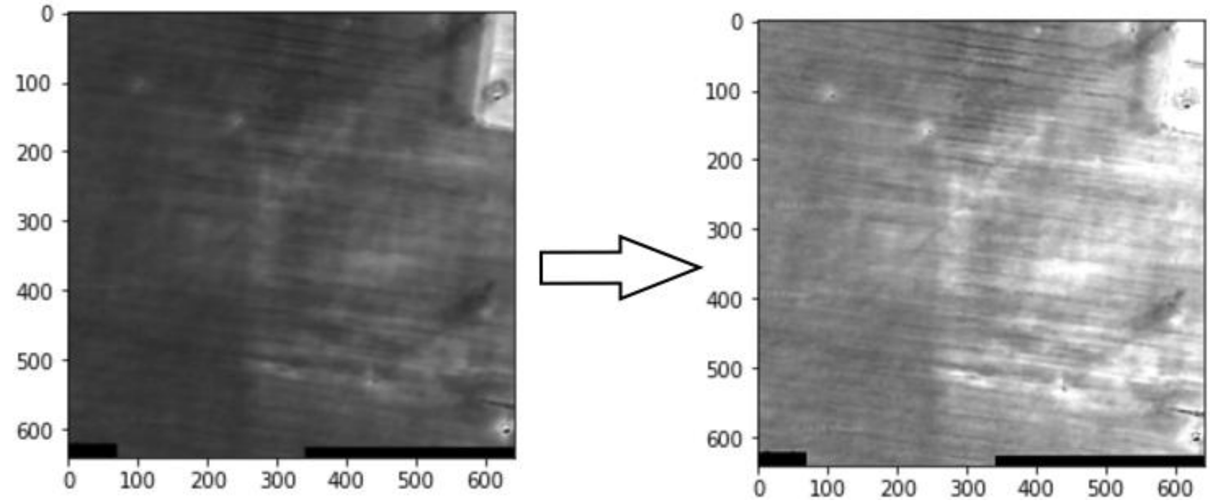

Fig. 1. **Adapting image brightness and contrast using 2D convolutional filtering**

The applied preprocessing process allowed to improve the contrast and visibility of details while preserving the spatial structure of the images, which ensured the compatibility of the input data with the PyCDA architecture. As a result, the adapted images became more similar to the training dataset of the model, which allowed its direct use for the detection of explosion craters in satellite images. An example of the identification of land plots damaged by explosions using transfer learning is shown in Fig. 2.

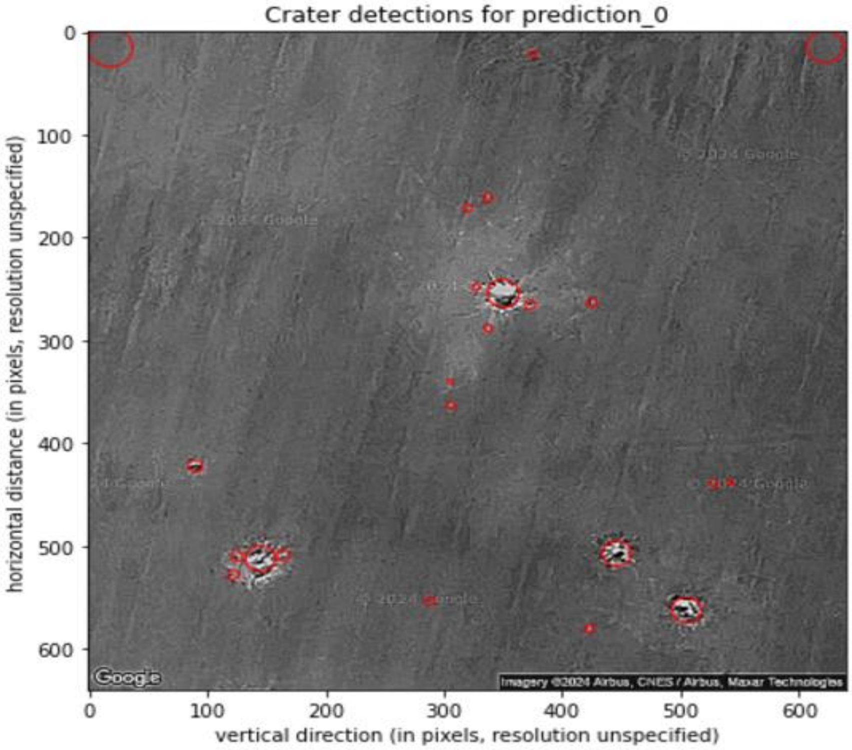

Fig. 2. **Detection of explosion craters using the PyCDA model**

The algorithm demonstrated complete coverage of the analysis area, insensitivity to variations in object sizes, and high accuracy of localization of detected craters. Changing the image zoom level has a limited effect on the Precision and Recall metrics. The mAP50 and mAP95 metrics show an increase with increasing zoom, indicating improved object localization under conditions of increased input detail. Similarly, increasing the number of training epochs to 100 provides an increase in complex metrics, but further training is not accompanied by a significant increase in the basic accuracy and completeness indicators.

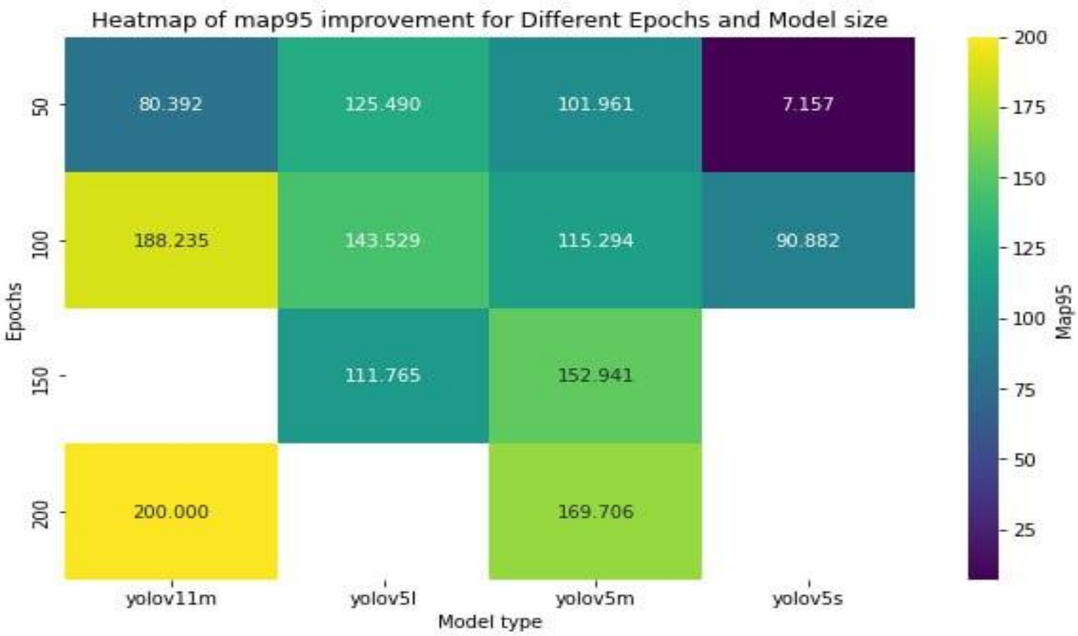

Fig. 3. **Generalized impact of data preparation and training parameters on the quality indicators of YOLO models**

Comparison of the basic augmentation with genetically optimized parameters showed that the optimized strategies provide stable growth of key metrics (especially in the lower quartiles), which is critical with a limited amount of data. The models of medium complexity – YOLOv5m and YOLOv11m – turned out to be the most stable at moderate computational costs (Fig. 3). According to the comparative analysis, YOLOv5m demonstrated the highest accuracy and speed. Its successful adaptation to crater detection was achieved by transfer learning on the PyCDA model, initially trained on planetary craters. Increasing the image scale (Zoom 17 → Zoom 19) increases mAP50/mAP95, while Precision and Recall remain stable. Increasing the number of epochs to 100 improves the metrics; further training does not give a significant increase in accuracy for YOLOv5m.

Particular attention within the study was focused on assessing the impact of augmentation strategies. A comparison was made between the basic approach (Default) and the optimized approach using genetic algorithms (Evolve) [10]. It was found that the use of Evolve provided a significant increase in all key accuracy metrics, including the lower quartiles of the distribution of results [11]. The data obtained confirm the importance of the choice of augmentation methods, especially in cases of limited training images. A separate study was conducted on the dependence of the quality of models on their architectural complexity [12]. Higher-level architectures, such as YOLOv5l, demonstrated potentially higher accuracy, however, in real-world conditions, models of medium complexity (YOLOv5m, YOLOv11m) turned out to be more stable in terms of results at moderate computational costs.

Conclusions

1. The study confirmed the effectiveness of artificial intelligence technologies for automated monitoring of degraded land resources in post-conflict regions. Based on the analysis of 9094 satellite images of different zoom levels (Zoom 17-19), it was found that the proposed system provides accuracy of identification of explosion craters at the level of 82-90%, depending on the visual noise conditions.
2. The advantage of the YOLOv5m architecture was experimentally proven, which demonstrated the optimal balance between detection accuracy and data processing speed compared to more complex YOLOv5l models and alternative architectures. The use of genetically optimized augmentation strategies (Evolve) provided a two-fold increase in accuracy metrics, with even the lowest indicators (first quartile) exceeding the highest results (third quartile) of standard image processing approaches.
3. Adaptation of the PyCDA model through transfer learning allowed to effectively transfer knowledge from the subject area of planetary geology to terrestrial monitoring tasks without the need to create an architecture from scratch. Further development of the research involves the integration of multispectral satellite imaging to improve the accuracy of classification of damage types and expand the functionality of the system to monitor natural recovery processes and ecosystem factors, in particular soil contamination by toxic substances.

Author contributions

Conceptualization, O.G.; methodology, I.B. and V.K.; software, R.R.; validation, O.T. and O.G.; formal analysis, O.G. and O.T.; investigation, O.G., I.B., V.K. and O.T.; data curation, I.B., O.G. and O.T.; writing – original draft preparation, O.G.; writing – review and editing, I.B. and O.G.; visualization, R.R. and V.K.; project administration, O.G.; funding acquisition, I.B. All authors have read and agreed to the published version of the manuscript.

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