

## A NEURAL NETWORK METHOD TO TRANSPORT INFRASTRUCTURE DAMAGE RECOGNITION DURING ARMED AGGRESSION USING SATELLITE IMAGES

**Kashtan V. Yu.** – PhD, Associate Professor, Associate Professor of Information Technology and Computer Engineering Department, Dnipro University of Technology, Dnipro, Ukraine. ROR: <https://ror.org/05hkn5555>. ORCID: <https://orcid.org/0000-0002-0395-5895>.

**Hnatushenko V. V.** – Dr. Sc., Professor, Head of Department of Information Technology and Computer Engineering, Dnipro University of Technology, Dnipro, Ukraine. ROR: <https://ror.org/05hkn5555>. ORCID: <https://orcid.org/0000-0003-3140-3788>.

### ABSTRACT

**Context.** Recognizing and analyzing changes in transport infrastructure using satellite imagery is important for urban planning, emergency management, military monitoring, and post-war reconstruction. Traditional methods of assessing the condition of roads and bridges, based on ground surveys and expert interpretation of aerial photographs, are labor-intensive, time-consuming, and potentially dangerous for personnel, especially during natural disasters or armed conflicts. In this regard, it is important to develop automated methods for detecting bridge damage using machine learning from publicly available satellite imagery.

**Objective.** This work aims to develop a neural network method for recognizing and pixel-localizing damage to transport infrastructure using Sentinel-2 multispectral images and OSM vector data, based on a modified Attention U-Net architecture with adaptive spatial-feature weighting and the Dice Loss function to produce a probabilistic damage mask.

**Method.** A method for recognizing damage to transport infrastructure in Sentinel-2 multispectral images and OSM vector data using a convolutional neural network is proposed. The method is based on the improved Attention U-Net neural network architecture, in which vector data of the transport network (linear road and railway axes, bridge contours) serve as a priori structural information about the geometry and spatial location of infrastructure objects. This information is used by the decoder's attention mechanism to limit the formation of output features to spatial areas corresponding to infrastructure objects. As a result, the loss function is calculated only within the spatial area specified by the binary mask of infrastructure objects. It reduces misclassifications in adjacent areas and increases the accuracy of boundary delineation for damaged bridge sections.

**Results.** Experimental studies have confirmed the effectiveness of the proposed method for automated detection of bridge damage on multispectral satellite images. The comprehensive use of spectral-temporal information, combined with binary masks of transport infrastructure, has reduced false classifications in adjacent areas and increased the accuracy of localizing damaged sections. According to the quantitative assessment results, the mIoU was 78.6%, the F1-score was 0.81, and the overall classification accuracy exceeded 93%.

**Conclusions.** The experiments confirmed the effectiveness of the proposed method for automated recognition of damage to road and railway bridges in satellite images. The improved Attention U-Net architecture, which combines spatial attention mechanisms with prior structural information about the transport network, has increased the accuracy of pixel-level damage area recognition compared to U-Net models. The proposed method enables the creation of analytical geospatial maps of damaged bridge sections, which can be directly integrated into geographic information systems for infrastructure monitoring, assessing the consequences of natural or military disasters, and supporting decision-making on response and recovery.

**KEYWORDS:** bridge damage, Attention U-Net, multispectral satellite imagery, deep neural networks, change detection, armed aggression.

### ABBREVIATIONS

OpenStreetMap is an OpenStreetMap;  
RGB is a red, green, blue color bands;  
NIR is a near-infrared spectral band;  
CNN is a convolutional neural network;  
FCN is a fully convolutional network;  
U-Net is a convolutional neural network architecture for fast and precise segmentation of images;  
Attention U-Net is a modified U-Net architecture with integrated attention gates;  
SAR is a synthetic aperture radar;  
ReLU is a Rectified Linear Unit;  
IoU is an intersection over union;  
PA is a pixel accuracy;  
mAP is a mean average precision;  
F1-Score is a harmonic mean of precision and recall;  
TP is a True Positive;  
TN is a True Negative;

FP is a False Positive;  
FN is a False Negative;  
CLAHE is a contrast limited adaptive histogram equalization.

### NOMENCLATURE

$X$  is a multispectral image;  
 $x_{ij}$  is a pixel of the image at position  $i, j$ ;  
 $\Omega$  is a spatial domain of the image;  
 $C$  is a set of spectral bands;  
 $B_2, B_3, B_4,$  and  $B_8$  are Sentinel-2 spectral bands (Blue, Green, Red, and Near-Infrared);  
 $V$  is a set of geospatial transport infrastructure objects;  
 $v_k$  is an individual transport object;  
 $F_\theta$  is a neural network model;  
 $\theta$  is a set of trainable model parameters;  
 $Y^*$  is a probabilistic damage mask;

$Y_{gt}$  is a ground truth mask;  
 $L(\cdot)$  is a loss function;  
 $\hat{S}_{i,j}$  is a binary damage mask;  
 $\tau$  is a decision threshold;  
 $X'$  is a training subsample;  
 $Y'$  is a corresponding output subsample;  
 $X_{in}$  is an input multispectral tensor;  
 $H$  is a spatial dimensions (height) of the image;  
 $W$  is a spatial dimensions (width) of the image;  
 $B$  is a number of spectral bands;  
 $x_{i,j}$  is a pixel of the image at position  $i, j$ ;  
 $\Omega$  is a spatial domain of the image;  
 $\Psi$  is a learnable parameters;  
 $G$  is a set of geospatial transport infrastructure objects;  
 $g_k$  is an individual transport infrastructure object;  
 $f(\cdot | \theta)$  is a neural network model;  
 $M_p$  is a probabilistic damage mask;  
 $M_{gt}$  is a ground truth damage mask;  
 $L(\theta)$  is a loss function;  
 $M_b$  is a binary damage mask;  
 $\tau$  is a decision threshold;  
 $S_{train}$  is a training subsample;  
 $Y_{train}$  is a corresponding output subsample;  
 $l$  is a index of the encoder-decoder level;  
 $x^l$  is a feature map at level  $l$ ;  
 $\sigma_R$  is a Rectified Linear Unit activation function;  
Pool is a MaxPooling operation;  
 $g$  is a gating signal from a deeper decoder layer;  
 $\alpha$  is an attention coefficient;  
 $\sigma_S$  is a Sigmoid activation function;  
 $p_i$  is a predicted probability for the  $i$ -th pixel;  
 $g_i$  is a ground truth value for the  $i$ -th pixel;  
 $\epsilon$  is a stabilization (smoothing) coefficient used in the loss function;  
 $L_{Dice}$  is a loss function;  
 $N$  is a number of image pixel categories;  
 $TP_i$  is a number of correctly classified pixels of class  $i$ ;  
 $FP_i$  is a number of false positive pixels for class  $i$ ;  
 $FN_i$  is a number of false negative pixels for class  $i$ ;  
 $T_i$  is a total number of pixels of class  $i$ .

## INTRODUCTION

The full-scale military invasion of Ukraine by the Russian Federation, which began on 24 February 2022, has led to widespread destruction of civilian and transport infrastructure across much of the country. As a result of intense fighting, road and rail bridges, road junctions, transport corridors, and ancillary infrastructure facilities that play a key role in ensuring the mobility of the population, the logistics of humanitarian aid, and the functioning of the economy have been destroyed or significantly damaged. The destruction of bridges and transport routes not only hinders the movement of the civilian population but also isolates settlements and disrupts connections between regions.

The problem is particularly acute in areas of active combat operations and in de-occupied territories, where

access for ground surveys is limited or dangerous. Physical inspection of the condition of bridges and roads under such conditions is associated with high risks to personnel, significant time costs, and substantial material resources. In addition, timely and reliable information on the extent and spatial location of damage to transport infrastructure is necessary for planning restoration work, assessing damage, securing humanitarian corridors, and making management decisions at the national and international levels. Under such conditions, there is an urgent need for rapid and reliable mapping of destroyed infrastructure facilities without the need to be physically present in dangerous areas.

The advancement of remote sensing technologies opens new opportunities for objective, large-scale analysis of the consequences of armed conflicts. Satellite imagery provides regular data updates, the ability to analyse large areas simultaneously, and access to multispectral information, making it an effective tool for detecting changes in land cover and damage to infrastructure. Of value in this context is data from Sentinel-2 satellites [1], which is publicly available, has medium spatial resolution, and a set of multispectral channels in the visible and near-infrared ranges.

The detection and analysis of transport infrastructure using satellite imagery is important for urban planning, emergency management, military monitoring, and post-war reconstruction. Sentinel-2 data enables the identification of road and bridge structures by exploiting the spectral contrast between the road surface and surrounding objects, as well as the analysis of changes in their condition over time. An analysis of scientific publications [2] shows that Sentinel-2 data is rarely used as the primary source of information for transport infrastructure detection and analysis tasks, yielding to datasets with high spatial resolution (less than 1 m), such as Cartosat [3], Massachusetts Roads [4], or DeepGlobe [5]. In addition, there are virtually no open annotated Sentinel-2 datasets specializing in the detection of road and bridge damage. It significantly complicates the training of deep learning models and necessitates the development of proprietary approaches to generating training samples and ground truth data. In this regard, it is relevant to develop a neural network approach to the spatial detection and localization of damage to transport infrastructure in combat conditions based on Sentinel-2 satellite images using modern deep learning architectures and auxiliary open geospatial data.

**The object of study** is the automated recognition and spatial localization of damage to transport infrastructure (roads and bridges) resulting from military operations, using multispectral satellite imagery.

**The subject of study** examines neural network methods for precise pixel-wise recognition and localization of damaged sections of transport infrastructure in multispectral Sentinel-2 imagery, using a modified Attention U-Net architecture with adaptive spatial-feature weighting.

**The purpose of the work** is to develop a neural network method for recognizing and pixel-localizing damage

to transport infrastructure using Sentinel-2 multispectral images and OSM vector data, based on a modified Attention U-Net architecture with adaptive spatial-feature weighting and the Dice Loss function to produce a probabilistic damage mask.

## 1 PROBLEM STATEMENT

Let  $X \in \mathbb{R}^{\{H \times W \times C\}}$  be a multispectral image defined on a spatial domain  $\Omega \subset \mathbb{Z}^2$ , where  $H$  and  $W$  denote the spatial dimensions of the image,  $C = \{B2, B3, B4, B8\}$  is the set of spectral channels corresponding to Sentinel-2 bands, and  $x_{\{i,j\}} \in \mathbb{R}^C$  is the spectral vector at spatial position  $(i, j) \in \Omega$ . Let  $V = \{v_k\}_{k=1}^K$  be a set of vector transport infrastructure objects obtained from OpenStreetMap and geospatially registered to  $\Omega$ , where each object  $v_k$  defines a spatial subset  $\Omega_k \subset \Omega$ . The objective is to synthesize a parameterized neural mapping  $F_\theta: (X, V) \rightarrow Y$ , where  $\theta$  is the set of trainable parameters, and  $Y = \{y_{\{i,j\}}\}_{(i,j) \in \Omega}$ ,  $y_{\{i,j\}} \in [0,1]$ , is a probabilistic damage mask. Given the ground truth mask  $Y_{gt} = \{g_{\{i,j\}}\}_{(i,j) \in \Omega}$ ,  $g_{\{i,j\}} \in \{0,1\}$ , the training problem is formulated as the optimization task  $\theta^* = \arg \min_\theta L(F_\theta(X, V), Y_{gt})$ , where  $L(\cdot, \cdot)$  is a loss function defined over  $\Omega$ . The binary damage mask  $\hat{S}$  is obtained by thresholding the probabilistic output such that  $\hat{S}_{\{i,j\}} = 1$  if  $y_{\{i,j\}} \geq \tau$  and  $\hat{S}_{\{i,j\}} = 0$  if  $y_{\{i,j\}} < \tau$ , where  $\tau \in (0,1)$  is a decision threshold. For training purposes, a spatial subsample  $\Omega' \subset \Omega$  is selected with  $|\Omega'| < |\Omega|$ . The corresponding training tensors are defined as  $X' = X|_{\Omega'}$  and  $Y'_{gt} = Y_{gt}|_{\Omega'}$ , and the loss function is minimized over  $\Omega'$  during model optimization.

## 2 REVIEW OF THE LITERATURE

Traditionally, the assessment of road and bridge conditions is based on ground observations and expert interpretation of aerial photographs, ensuring high accuracy at the local level. However, such approaches are labor-intensive, time-consuming, and potentially unsafe for personnel, especially in the context of natural disasters or armed conflicts. In this regard, methods for automated analysis of Earth remote sensing data have undergone significant development, enabling spatially coordinated assessment of the condition of transport infrastructure at the regional and interregional levels. Recent studies have focused on the use of optical and radar satellite images, combined with machine learning and deep learning algorithms, for automated detection of changes and damage to infrastructure objects.

Existing approaches to detecting and assessing road damage can be divided into three groups depending on the type of input data used. The first group consists of methods based on medium-resolution optical satellite imagery, in particular Sentinel-2 data, which provide regular coverage of large areas and enable the analysis of the spectral and spatial features of infrastructure objects. Such approaches primarily focus on regional mapping of road changes and damage, using convolutional neural networks (CNNs) for defect segmentation and classification. Scien-

tists often describe road segmentation tasks on Sentinel-2 data [6] in general, and some recent publications have developed special datasets and methods for this task. For example, the Sentinel-2 Roads Dataset was created, which contains road segmentation masks combined with OpenStreetMap data to build training samples, enabling the investigation of the effectiveness of different road segmentation models specifically on Sentinel-2 images with a resolution of 10 m or higher. It has been shown that pre-processing (gamma correction, CLAHE) improves segmentation results [7]. In [8], a multi-level approach is proposed for the quantitative assessment of infrastructure damage after natural disasters in Ukraine, combining medium-resolution remote sensing data with multi-layer deep learning models. In this context, Sentinel-2 spectral features together with CNN architectures are used to segment damaged sections of roadways and bridge structures.

The second group consists of methods that use high- and ultra-high-resolution images obtained from aerial photography [9] or commercial satellite platforms. Thanks to their high spatial resolution, such data enable more accurate reconstruction of the geometry of road elements and local pavement defects. In [10], a hybrid method that synthesizes segmentation and tracing approaches is proposed to solve the problem of road network connectivity loss during automatic extraction. The authors use a fully convolutional network (FCN) for initial road-surface segmentation, followed by iterative refinement with a “lightweight” FCN architecture to improve object-localization accuracy. An experimental evaluation of satellite images of cities demonstrated the advantage of this approach, particularly an 8% increase in the IoU metric compared to traditional tracing methods. In [11], a hybrid CNN model was developed using Gabor filters to detect road and building damage in high-resolution satellite images simultaneously. Similarly, modified versions of YOLO models proposed in [12–14] demonstrated higher F1 scores and mean average precision (mAP) in detecting road surface damage in high-resolution images.

The third group includes multimodal approaches that combine optical and radar images, digital terrain models, and vector geospatial data. The integration of different sources of information improves the robustness of automated algorithms to noise, lighting changes, and complex backgrounds. Works [15, 16] demonstrate the effectiveness of deep fully convolutional neural networks (FCNNs) for segmenting thin linear objects in SAR images, which is important for extracting roads under radar distortion. The authors’ research in [17] demonstrates the feasibility of integrating optical and radar data to improve the accuracy of detecting road network objects in an urban environment. In addition, the use of digital terrain models, for detecting flooded road sections, was demonstrated in [18].

An analysis of existing studies reveals limitations: first, in most works, the architecture of neural models lacks explicit mechanisms for detecting changes over time, and damage assessment is based primarily on the

analysis of individual images or on implicit comparisons of multi-temporal data. Second, there are few studies devoted to the creation and publication of standardized, annotated datasets based on medium-resolution satellite imagery, and there is a lack of ready-to-analyze data suitable for automated road damage detection. Taking together, these limitations necessitate the development of a neural network approach focused on the explicit detection and spatial localization of changes using temporally consistent multispectral satellite images, accounting for vector descriptions of transport infrastructure objects and a formalized procedure for preparing training data.

### 3 MATERIALS AND METHODS

Within the scope of this study, transport infrastructure objects are defined as motorways, transport bridges, and railway bridges. The neural network method proposed in this work focuses on automated recognition and spatial localization of damage to transport infrastructure objects using multi-temporal, multispectral Sentinel-2 satellite images and OpenStreetMap vector data. The general scheme of the approach is shown in Fig. 1. It includes the stages of preliminary processing of input data, formation of a training sample, application of a neural network architecture, and creation of a probabilistic damage mask.

The first stage is to download multi-temporal Sentinel-2 images obtained before and after the destruction event, and to reduce them to a single discrete area.

The second stage is the preprocessing of the satellite images loaded in the first stage to ensure correct analysis of changes: geometric correction aimed at spatial alignment of images taken at different times and elimination of shifts between pixels; radiometric correction, which ensures the normalization of brightness characteristics, taking into account the shooting conditions; spectral correction aimed at coordinating individual spectral channels regardless of seasonal and angular shooting conditions [19].

The third stage involves forming an input tensor by selecting Sentinel-2 spectral bands: B2 (Blue), B3 (Green), B4 (Red), and B8 (Near-Infrared, NIR). The selection of these channels is due to their high spatial resolution (10 m/ m/pixel) and the physical properties of the infrastructure object's reflection. The visible range of channels (B2, B3, B4) provides detailed visual information about the texture and geometric integrity of the bridge deck. The near-infrared channel (B8), thanks to its high spectral differentiation, allows distinguishing between artificial materials (concrete, asphalt) and natural objects (water, vegetation). It allows the model to clearly distinguish the bridge structure from the water surface even in conditions of temporary flooding or shading.

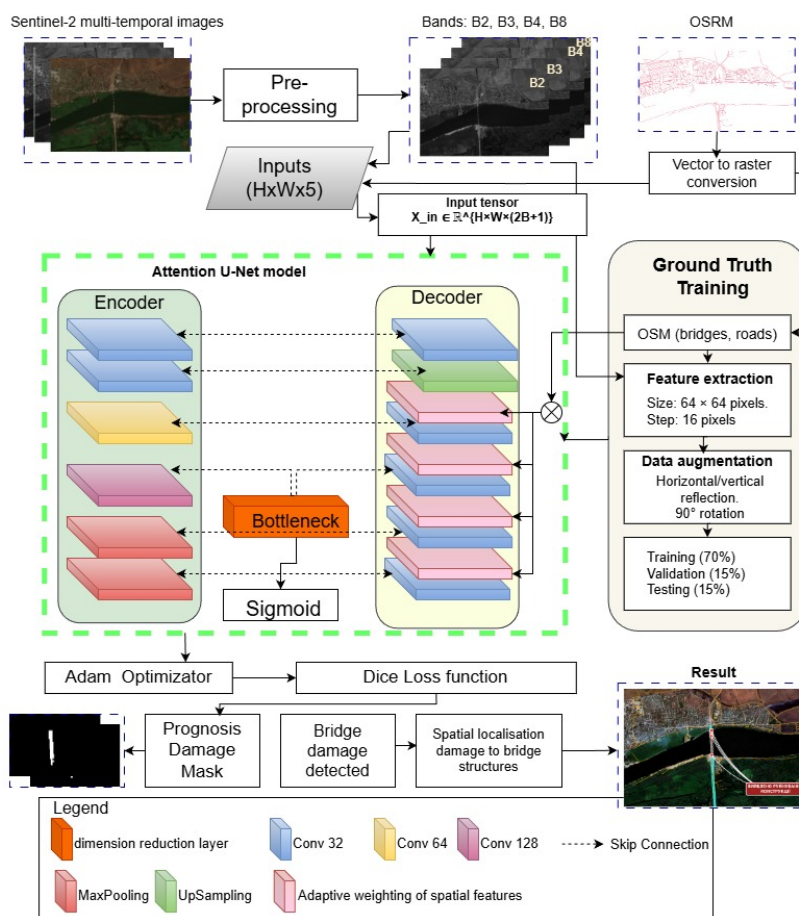


Figure 1 – Diagram of the proposed method for the detection and spatial localization of damage to transport infrastructure

The fourth stage, in parallel with satellite image preparation, involves loading and processing vector data on road infrastructure from the OpenStreetMap service [20] using OSRM tools. This process is important for creating a reference mask (Ground Truth Training). At this stage, vector objects of the bridge and highway classes are extracted for the area of interest. Since the neural network operates on matrices, the vectors are converted to a raster mask, with pixels corresponding to the infrastructure assigned a value of 1 and the background assigned a value of 0. The resulting raster mask is reduced to the same discrete area as the satellite data, ensuring pixel-by-pixel correspondence.

In the fifth stage, the input tensor  $X_{in}$  is formed by combining spectral channels ( $B_2, B_3, B_4, B_8$ ) with the raster-converted results of OSM vector layers. The structure of the input data is described by equation (1):

$$X_{in} \in \mathbb{R}^{H \times W \times (2B+1)}. \quad (1)$$

In the sixth stage, a structured dataset was created for training the neural network. Given the high resolution of the input data and limited computing resources, multispectral images and their corresponding Ground Truth masks were segmented into fixed-size patches. A sliding window method with a size of 64 by 64 pixels and a step of 16 pixels is used (feature extraction process). Such overlap preserves the spatial continuity of infrastructure objects and increases the number of training examples. To increase the model's resistance to geometric variations and prevent overfitting, real-time augmentation methods are used. The formed dataset is divided into subsets: training – for direct correction of network weight coefficients; validation – for monitoring the training process and adjusting hyperparameters; test – for the final assessment of the model's generalization ability on data that was not used during training.

To detect damage, the seventh stage uses a modified Attention U-Net architecture [21] that combines a classic encoder-decoder architecture with an attention mechanism. The choice of Attention U-Net architecture for this task is driven by the need to recognize complex-geometry objects (bridges) against a spectrally similar background. The main advantage of this model is the integration of attention mechanisms (Attention Gates) into the standard U-Net architecture, enabling the network to automatically focus on target structures and minimize the weights of non-informative features without increasing computational complexity. The encoder performs sequential feature extraction by compressing the spatial dimension of the input tensor  $X_{in}$ :

$$X_{in} \in \mathbb{R}^{H \times W \times 9}.$$

Each encoder level consists of convolutional layers (Conv 32, 64, 128 filters). Mathematically, the output of each encoder block  $l$  is described by equation (2) [20]:

$$x^l = Pool(\sigma(W^l * x^{l-1} + b^l)). \quad (2)$$

The decoder is responsible for restoring the spatial dimension using Up-sampling operations. Unlike the classic U-Net, this paper proposes an adaptive weighting mechanism for spatial features. Before combining features via Skip Connections, the data passes through attention blocks (AGs) that use the getting signal  $g$  from a deeper layer of the decoder to filter features  $x^l$  from the encoder. The attention coefficient  $\alpha$  is calculated using formula (3) [20]:

$$\alpha^l = \sigma_2(\Psi^T(\sigma_1(W_x^T x^l + W_g^T g + b_g)) + b_\psi). \quad (3)$$

At the bottom of the feature hierarchy is the Bottleneck block, which acts as a connecting element between the encoder and decoder. It ensures maximum compression of spatial information, forming a compact representation of abstract object features in a low-dimensional vector. After passing through the recovery path (decoder), the final segmentation is performed using the output layer with the Sigmoid activation function, which forms a probabilistic damage mask:

$$P(y=1|x) = \frac{1}{1 + e^{-z}}.$$

To minimize errors and correctly update network weights, the Adam optimizer is used, which determines the learning rate for each weight coefficient based on gradient moment estimates. Given the significant imbalance between the pixels of target objects (destruction) and the background, a common problem in recognizing transport infrastructure in satellite images, the Dice Loss function [22] was selected for model training. This approach ensures stable network optimization by maximizing the similarity coefficient between the predicted and reference masks according to formula (4) [21]:

$$L_{Dice} = 1 - \frac{2 \sum_{i=1}^N p_i g_i + \epsilon}{\sum_{i=1}^N p_i^2 + \sum_{i=1}^N g_i^2 + \epsilon}. \quad (4)$$

At the final stage, the probability mask is spatially localized by comparing it with raster infrastructure masks generated from OSM data. It allows damage and accurately linking it to the object's geographical coordinates.

The result is a multispectral image with the Damage Mask layer overlaid, clearly highlighting the damage contours against the background of the bridge's structural elements. It provides a visual interpretation of the object's condition and enables the data obtained to be used for operational decision-making regarding infrastructure restoration.

#### 4 EXPERIMENTS

Experimental research was conducted in the Kherson region, which suffered significant damage to its transport infrastructure due to hostilities. The Antonivsky automobile bridge and the Antonivsky railway bridge, which are important elements of the region's transport network, were selected as test objects. The analysis used multispectral Sentinel-2 satellite images (10 m spatial resolution)

acquired in September 2021, before the start of hostilities, and in September 2023, after the destruction of the bridge structures. The use of this particular period allows for minimizing seasonal differences in spectral characteristics and ensuring the correct detection of changes related to destruction.

Reference masks of destruction were generated from manual visual interpretation of Sentinel-2 satellite images acquired at different times, using scenes “before” and “after” the event. The annotation procedure was based on the analysis of spatial gaps, geometric deformations, and changes in the spectral characteristics of bridge structures, and was also confirmed by open-source information. This method ensures high-quality annotations specifically for narrow linear transport infrastructure objects. The images were divided into  $64 \times 64$ -pixel fragments. The resulting dataset was divided into a training sample (70%), a training (validation) sample (15%), and a test sample (15%). The training sample was used to optimize the neural network weights, the validation sample to select hyperparameters and control overfitting, and the test sample to evaluate the model’s generalization. To improve the model’s stability, data augmentation methods were used, in particular, rotation, reflection, and scaling of image fragments.

The neural network models were trained until the loss function stabilized on the validation sample. To evaluate the effectiveness of the proposed method, a comparison was made with the following architectures: the basic U-Net model, the classic Attention U-Net, and the proposed structure-aware Attention U-Net using a structural mask of the transport infrastructure. Thus, experimental studies aim not only to achieve high absolute metric values but also to analyze the impact of attention mechanisms and structural information on damage recognition quality. To quantitatively evaluate the segmentation results, a set of standard metrics was used, which are most informative for the task of pixel-level segmentation of transport infrastructure objects.

Pixel Accuracy (PA) determines the proportion of correctly classified pixels relative to the total number of pixels in the image using formula (5) [23]:

$$PA = \frac{TP}{TP + FP + FN + TN} \quad (5)$$

Pixel accuracy allows you to evaluate how well the model copes with the classification of each pixel, which is vital for segmentation at the level of a detailed image and for the accurate selection of vehicles in satellite images.

The Intersection over Union (IoU) metric is important for evaluating the accuracy of damage localization, as it directly accounts for both omissions and over-segmentation [23]:

$$MA = \frac{1}{N} \sum_{i=1}^N \frac{TP_i}{TP_i + FP_i + FN_i}$$

Using the F1-Score metric allows for a balanced assessment of segmentation quality in conditions of significant imbalance between the “destruction” and “background” classes. Precision and Recall metrics are vital for practical transport infrastructure monitoring systems, as a high Precision value reduces the number of false alarms. In contrast, a high Recall ensures that the maximum number of real damages are detected. Within the scope of the experiments, the primary focus was on the ability of models to correctly localize damage in bridge structures, reduce the number of false positives outside the transport infrastructure, ensure stable training, and avoid overfitting.

Thus, the above-described set of quantitative metrics enables a comprehensive assessment of both the recognition accuracy and the practical applicability of the proposed neural network method for automated monitoring of damage to transport infrastructure.

## 5 RESULTS

The proposed neural network method for detecting damage to transport infrastructure was tested experimentally on two critical infrastructure facilities in the Kherson region: the Antonivsky road bridge (Fig. 2) and the Antonivsky railway bridge (Fig. 3).



Figure 2 – Multi-temporal Sentinel-2 images of the Antonivsky Bridge: a – 2021 before destruction; b – 2023 after destruction



Figure 3 – Multi-temporal Sentinel-2 images of the Antonivsky Railway Bridge: a – 2021 before destruction; b – 2023 after destruction

For each facility, multi-temporal multispectral Sentinel-2 satellite images were used, reflecting the state of the infrastructure before the start of hostilities (October 2021) and after the destruction (October 2023). The analysis was performed to automatically detect and spatially locate areas of structural damage in bridges.

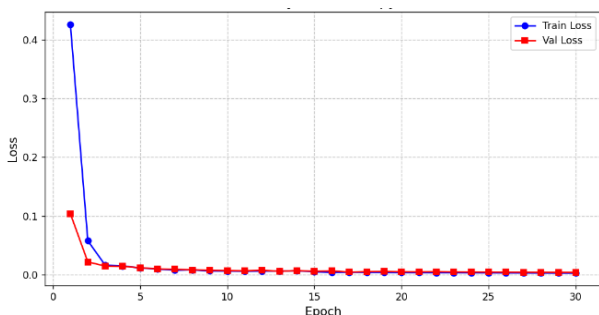


Figure 4 – Training a proposed modified Attention U-Net model

Table 1 shows the generalized values of the main performance metrics for the training and validation samples.

Table 1 – Evaluation metrics of the modified Attention U-Net architecture

Metrics	Accuracy (training)	Accuracy (validation)
Accuracy	0.95	0.95
Binary Crossentropy (Loss)	0.005	0.005
Precision	0.96	0.95
Recall	0.94	0.93
F1-Score	0.95	0.94

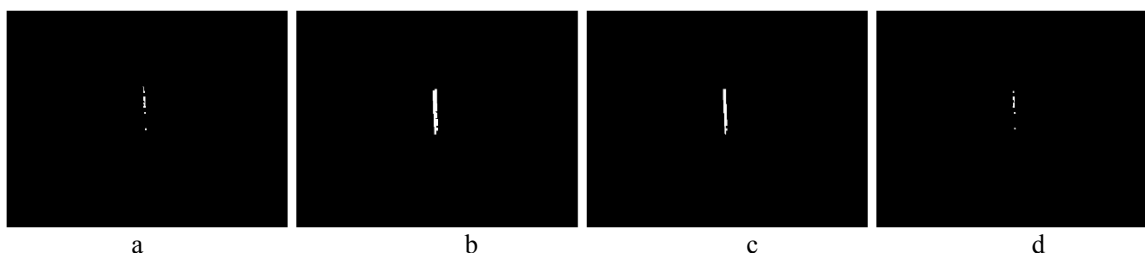


Figure 5 – Binary mask with damage polygons on the Antonivsky Bridge: a – reference binary damage mask; b – U-Net architecture; c – Attention U-Net architecture; result – proposed modified Attention U-Net architecture

The accuracy of damage recognition was evaluated by analyzing the error matrix derived from pixel-by-pixel classification of damage areas for both bridge structures. To quantitatively evaluate the effectiveness of the proposed method, comparisons were made with the basic U-Net architecture and the classic Attention U-Net. The comparison results are shown in Table 2.

Table 2 – Comparative analysis of damage detection accuracy for different architectures

Model	IoU	F1-score	Precision	Recall
Antonivsky Bridge				
U-Net (baseline)	0.68	0.76	0.71	0.82
Attention U-Net	0.74	0.83	0.79	0.88
Proposed	0.89	0.94	0.96	0.93
Antonivsky Railway Bridge				
U-Net (baseline)	0.11	0.12	0.12	0.11
Attention U-Net	0.15	0.37	0.21	0.15
Proposed	0.97	0.98	0.98	0.97

The results of the detection of damage to bridge structures are presented in the form of binary masks with polygons of damaged areas for the Antonivsky automobile bridge (Fig. 5) and the Antonivsky railway bridge (Fig. 6). For each object, the following are provided: a reference binary mask of damage; the result of damage recognition by the U-Net architecture; the result of Attention U-Net; the result of the proposed modified Attention U-Net. For the Antonivsky automobile bridge, the following damage recognition values were obtained: for the U-Net model – IoU = 0.17, Precision = 0.17; for Attention U-Net – IoU = 0.22, Precision = 0.23; for the proposed modified Attention U-Net – IoU = 0.79, Precision = 0.96.

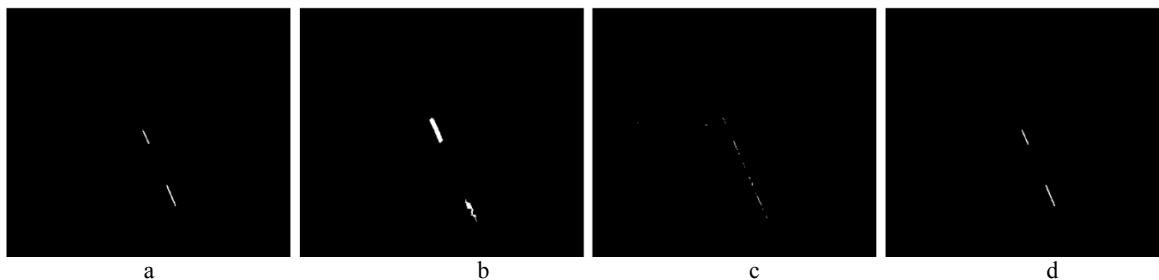


Figure 6 – Binary mask with damage polygons on the Antonivsky railway bridge: a – reference binary damage mask; b – U-Net architecture; c – Attention U-Net architecture; result – proposed modified Attention U-Net architecture

For the Antonivsky Railway Bridge, the corresponding metric values are: U-Net – IoU = 0.11, Precision = 0.13; Attention U-Net – IoU = 0.15, Precision = 0.37; proposed modified Attention U-Net – IoU = 0.98, Precision = 0.98. Binary masks were used to generate vector

polygons of damage areas, reflecting the spatial locations of damaged bridge sections. Since the task of detecting damage is formalized as pixel-by-pixel recognition of damaged areas, the model’s quality was evaluated using an error matrix (Fig. 7).

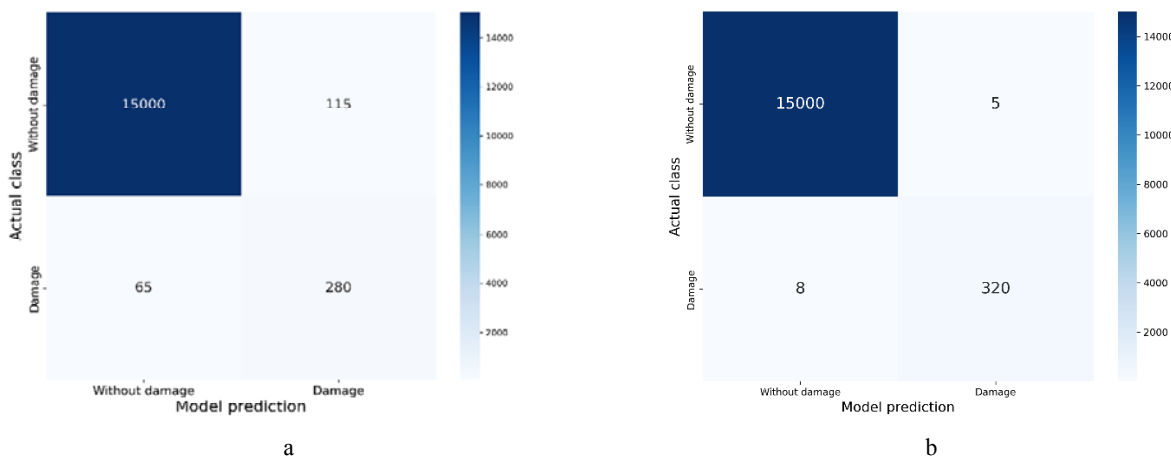


Figure 7 – Confusion matrices: a – detection of damage on the Antonivsky automobile bridge; b – detection of damage on the Antonivsky railway bridge

The final results of damage recognition are presented as analytical geospatial maps generated from binary masks. Separate maps were created for the Antonivsky Road Bridge (Fig. 8a) and the Antonivsky Railway Bridge (Fig. 8b), showing the spatial location of the detected damage areas. The analytical map for the An-

tonivsky railway bridge shows the areas of structural integrity violations corresponding to the areas of bridge structure breaks. A similar map for the Antonivsky road bridge shows the spatial configuration of damaged segments along the bridge axis.



Figure 8 – The result of the proposed neural network method for damage detection in 2023: a – Antonivsky automobile bridge; b – Antonivsky railway bridge

## 6 DISCUSSION

The results obtained demonstrate the effectiveness of the proposed neural network method for pixel-by-pixel detection and spatial localization of bridge damage using Sentinel-2 multispectral satellite images. High values of generalized quality metrics for the training and validation samples are shown in Table 1, where the Accuracy is 0.99 for both. The values of the Binary Crossentropy loss function are 0.0045 for the training sample and 0.0048 for the validation sample. The Precision, Recall, and F1-score metrics for the validation sample are 0.95, 0.93, and 0.94, respectively, indicating the quality of pixel-level recognition of damage areas.

Figure 4 shows the dynamics of training the Structure-Aware Attention U-Net model over 30 epochs. For both research objects, there is a rapid decrease in the loss function values during the first 5 epochs, indicating the correctness of the input data and the effectiveness of the selected optimization strategy. The stabilization of the training and validation curves at low values confirms the absence of overfitting.

The results of bridge damage detection are presented as binary masks with polygons of damaged bridge sections (Fig. 5 and Fig. 6). For each object, reference binary masks, segmentation results from the basic U-Net architecture, the Attention U-Net, and the proposed modified Attention U-Net are provided. A comparative analysis with the basic U-Net architecture and the classic Attention U-Net showed a significant increase in segmentation accuracy when using the proposed modified Attention U-Net. The difference is particularly pronounced for a complex object the Antonivsky Railway Bridge, where traditional architectures demonstrate low IoU and F1-score values. It indicates the limited ability of standard approaches to correctly identify narrow, elongated, and structurally heterogeneous objects in scenes with moderate spatial diversity.

Visual analysis of binary masks (Fig. 4 and Fig. 5) and the formed polygons confirms the quantitative results. For the railway bridge, the proposed method clearly reproduces the spatial configuration of the extensive, fragmented structural breaks. For the road bridge, the model correctly localizes the damaged segments along the structure's axis, indicating the architecture's ability to account for the object's structural features rather than just local spectral differences.

The increase in IoU and Precision (Table 3) for the proposed architecture indicates reduced false positives and more accurate contouring of damage areas. It is essential for infrastructure damage analysis tasks, where even a slight shift in segment boundaries can lead to significant errors during subsequent mapping or damage assessment.

Analysis of error matrices (Fig. 7) confirms that the task of detecting damage to transport infrastructure can be correctly formalized as a pixel-by-pixel classification task within the framework of semantic segmentation. The dominance of correctly classified background pixels, while maintaining high sensitivity to the "destruction"

class, indicates that the model is balanced across both classes and does not excessively increase the number of false-positive background pixels, a typical problem in tasks with significantly unbalanced data.

The formation of final analytical geospatial maps (Fig. 8a and Fig. 8b) based on vectorized results demonstrates the applied value of the proposed method.

The results of the spatial localization of the destruction of the Antonivsky automobile bridge (Fig. 8a) are presented as four discrete polygons of damaged areas, whose locations are consistent with the reference data. The resulting polygons reflect local changes in the structural and textural characteristics of the transport structure's surface associated with the violation of the bridge's integrity. The use of spatial attention mechanisms (Attention Gates) within the proposed architecture ensured the prioritized processing of features relevant to the areas of destruction. It reduced the impact of seasonal fluctuations in water levels and of shadow effects from load-bearing structures.

The map of the Antonivsky Railway Bridge (Fig. 8b) clearly identifies areas where structural elements are broken. Of scientific interest is the model's ability to differentiate small-area linear objects, despite the railway track being represented as a narrow, pixel-by-pixel linear segment in Sentinel-2 images. The improved proposed modified Attention U-Net architecture ensures correct localization of structural breaks by reducing false positives in areas with spectrally similar water surfaces. The result confirms the hypothesis that using OpenStreetMap vector masks as a priori structural constraint minimizes the effect of spectral mixing characteristic of classical pixel segmentation methods.

## CONCLUSIONS

The paper develops and experimentally tests a neural network method for the automated detection and spatial localization of damage to transport infrastructure objects using multi-temporal, multispectral Sentinel-2 satellite images and OpenStreetMap vector data. The research was conducted using the example of the Antonivsky automobile and railway bridges in the Kherson region, which enabled analysis of the effectiveness of the method for linear infrastructure objects with different structural and spatial organizations.

The proposed modified Attention U-Net architecture, which combines spatial attention mechanisms with a priori structural information about the transport network, achieved a significant increase in the accuracy of pixel-level recognition of damage areas compared to the basic U-Net and the classic Attention U-Net. The obtained values of IoU, Precision, and F1-score metrics confirm the model's ability to correctly localize damaged areas even under conditions of limited spatial separation of images and the presence of spectrally similar background surfaces.

**The scientific novelty** of this study lies in the development of a method for recognizing and pixel-level localizing damage to transport infrastructure in Sentinel-2 mul-

tispectral images and OSM vector data using a convolutional neural network. An improved architecture of the Attention U-Net neural network is proposed, in which vector data from the transport network (linear road and railway axes, bridge contours) serve as a priori structural information about the geometry and spatial location of infrastructure objects. This information is used by the decoder's attention mechanism to limit the formation of output features to spatial areas corresponding to infrastructure objects. As a result, the loss function is calculated only within the spatial area specified by the binary mask of infrastructure objects. Unlike traditional approaches, the proposed method uses multi-temporal multispectral images pre-aligned in a standard spatial coordinate system and accounts for intertemporal changes in spectral brightness across Sentinel-2 channels (B2, B3, B4, B8). The obtained spectral information is integrated with binary masks of bridges, thereby reducing misclassifications in adjacent areas and increasing the accuracy of boundary detection for damaged bridge sections.

**The practical significance** of the proposed method lies in its automated, accurate detection of damage to transport infrastructure using open satellite data. The method enables the creation of analytical geospatial maps of damaged bridge sections, which can be directly integrated into geographic information systems for infrastructure monitoring, assessing the consequences of natural or military disasters, and supporting decision-making on response and recovery.

**Prospects for further research** include applying the proposed method using new approaches to data processing and analysis, additional sources of information such as SAR images and high-resolution optical images, and optimizing attention mechanisms to improve the accuracy of transport infrastructure condition assessment using high-resolution data.

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#### DECLARATIONS

**Conflict of interest:** The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship, or otherwise, that could affect the research and its results presented in this paper.

**Authors' contributions:** Vita Kashtan: the method for recognizing and pixel-level localizing damage to transport infrastructure in Sentinel-2 multispectral images and OSM vector data using a convolutional neural network; Volodymyr Hnatushenko: experimental study of training sample selection method.

**Data availability:** The manuscript has no associated data.

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**Use of artificial intelligence tools:** The authors used Grammarly to check the grammar and spelling. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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## НЕЙРОМЕРЕЖЕВИЙ МЕТОД РОЗПІЗНАВАННЯ РУЙНУВАНЬ ТРАНСПОРТНОЇ ІНФРАСТРУКТУРИ В УМОВАХ ЗБРОЙНОЇ АГРЕСІЇ З ВИКОРИСТАННЯМ СУПУТНИКОВИХ ЗНІМКІВ

**Каштан В. Ю.** – канд. техн. наук, доцент, доцент кафедри інформаційних технологій та комп'ютерної інженерії Національного технічного університету «Дніпровська політехніка», Дніпро, Україна. ROR: <https://ror.org/05hkn5555>. ORCID: <https://orcid.org/0000-0002-0395-5895>.

**Гнатушенко В. В.** – д-р техн. наук, професор, завідувач кафедри інформаційних технологій та комп'ютерної інженерії, Національного технічного університету «Дніпровська політехніка», Дніпро, Україна. ROR: <https://ror.org/05hkn5555>. ORCID: <https://orcid.org/0000-0003-3140-3788>.

### АНОТАЦІЯ

**Актуальність.** Розпізнавання та аналіз змін транспортної інфраструктури за супутниковими знімками має важливе значення для задач міського планування, управління надзвичайними ситуаціями, військового моніторингу та післявоєнного відновлення. Традиційні методи оцінки стану доріг і мостів, що базуються на наземних обстеженнях та експертній інтерпретації аерофотознімків, є трудомісткими, часовитратними та потенційно небезпечними для персоналу, особливо в умовах стихійних лих або збройних конфліктів. У зв'язку з цим актуальним є розроблення автоматизованих методів виявлення руйнувань мостів на основі відкритих супутникових даних із використанням методів машинного навчання.

**Мета роботи** – розробка нейромережевого методу розпізнавання та піксельної локалізації руйнувань транспортної інфраструктури на основі багатоспектральних знімків Sentinel-2 та векторних даних OSM з використанням модифікованої архітектури Attention U-Net з адаптивним зважуванням просторових ознак та використанням функції Dice Loss для формування імовірнісної маски пошкоджень.

**Метод.** Запропоновано метод розпізнавання зон руйнувань транспортної інфраструктури на основі багатоспектральних знімків Sentinel-2 та векторних даних OSM із застосуванням згортової нейронної мережі. Метод базується на вдосконаленій архітектурі нейронної мережі Attention U-Net, у якій векторні дані транспортної мережі (лінійні осі доріг і залізниць, контури мостів) використовуються як джерело апріорної структурної інформації про геометрію та просторове розташування інфраструктурних об'єктів. Ця інформація використовується в механізмі уваги декодера та дозволяє обмежувати формування вихідних ознак лише просторовими зонами, що відповідають інфраструктурним об'єктам. У результаті функція втрат обчислюється лише в межах просторової області, заданої бінарною маскою інфраструктурних об'єктів. Це дозволяє зменшити кількість помилкових класифікацій у прилеглих зонах та підвищує точність визначення границь пошкоджених ділянок мостів.

**Результати.** Експериментальні дослідження підтвердили ефективність запропонованого методу автоматизованого виявлення руйнувань мостів на багатоспектральних супутникових знімках. Комплексне використання спектрально-часової інформації з бінарними масками транспортної інфраструктури дозволило зменшити кількість помилкових класифікацій у прилеглих зонах та підвищити точність локалізації пошкоджених ділянок. За результатами кількісної оцінки досягнуто значення mIoU на рівні 78,6%, F1-score – 0,81, а загальна точність класифікації (Overall Accuracy) перевищує 93%.

**Висновки.** Проведені експерименти підтвердили ефективність запропонованого методу автоматизованого розпізнавання руйнувань автомобільних і залізничних мостів на супутникових знімках. Вдосконалена архітектура Attention U-Net, яка поєднує механізми просторової уваги з апріорною структурною інформацією про транспортну мережу, забезпечила підвищення точності попиксельного розпізнавання зон руйнувань порівняно з моделями U-Net. Запропонований метод дозволяє створювати аналітичні геопросторові карти пошкоджених ділянок мостів, які можна безпосередньо інтегрувати в географічні інформаційні системи для моніторингу інфраструктури, оцінки наслідків катастроф природного або воєнного походження та підтримки прийняття рішень щодо реагування і відновлення.

**КЛЮЧОВІ СЛОВА:** руйнування мостів, Attention U-Net, багатоспектральні супутникові знімки, глибокі нейронні мережі, виявлення змін, збройна агресія.

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