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AUTOMATED SYSTEM FOR DAMAGE ANALYSIS OF URBAN INFRASTRUCTURE OBJECTS USING COMPUTER VISION MODELS

The current problem is to ensure the integration of multi-level data for effective monitoring and analysis of damage to buildings resulting from military operations in Ukraine, and to determine restoration priorities. The purpose of this work is to develop an intelligent system for automated analysis of damage to urban infrastructure objects, enabling effective processing of large volumes of images obtained using computer vision tools for further assessment of the level of destruction and decision-making regarding the priority of their restoration. The detailed reports generated by the system on each building's condition significantly simplify the expert evaluation process, eliminating the need for specialists to be physically present on-site. Ranking damaged objects by their impact on the country's vital activities ensures a more rational, well-balanced allocation of the resources required for infrastructure restoration. In addition, the system actively interacts with relevant state structures, local governments and specialists responsible for planning and organizing restoration work. Within the framework of such interaction, it is envisaged to obtain access to comprehensive databases with information on the architectural features of buildings, their historical and cultural value, as well as the use of existing technical documentation, which makes it possible to take into account all aspects when assessing the severity of damage and forming building restoration plans. Analysis of data obtained from specialised engineering surveys and studies using high-precision instrumental methods enables additional refinement of damage parameters and the creation of extended datasets for further training and validation of computer vision models. The paper investigates and justifies the feasibility of using instance segmentation with YOLOv11 and Mask R-CNN models, enabling not only damage detection but also accurate boundary and quantity determination, which is important for a comprehensive assessment of the scale of destruction and planning restoration measures. The results show that the proposed system works effectively when approaches to combat class imbalance are used. An important stage of the system is the automated formation of optimized restoration plans based on a comprehensive analysis of the identified damage. Such plans should take into account not only the technical parameters of the destruction, but also financial, material and personnel limitations. The proposed system is an effective tool for supporting decision-making at the state and regional levels on the restoration of damaged structures, contributing to the acceleration of the restoration processes of critical infrastructure and minimizing socio-economic losses associated with military destruction.

Keywords: damage analysis; urban infrastructure; deep learning; computer vision models; instance segmentation; image set; intelligent system.

1. Introduction

As a result of the armed aggression launched by the armed forces of the Russian Federation in 2022, the infrastructure of many settlements in Ukraine has suffered significant damage. This has disrupted the normal functioning of residential infrastructure, reduced the quality of life for residents, and led to the loss of cultural and historical heritage. There is an urgent need for the effective restoration of damaged structures, and the issue of prioritizing such restoration becomes particularly important given the limited availability of necessary resources.

To determine the order of restoration, it is necessary to consider the extent of physical damage to the facilities, structural features, social role, and cultural and historical value of the destroyed buildings. Traditional methods of damage assessment, based on expert inspections, are labor-intensive and typically subjective. Given the significant number of damaged structures across the country, it is advisable to improve approaches to analyzing the extent of infrastructure damage and planning the corresponding restoration work. In doing so, the task of restoring destroyed and damaged structures must be considered both during the war and in the post-conflict period. It should be noted that, given the ongoing hostilities, there is a threat to workers performing restoration work, as well as the risk of new destruction.

Currently, Ukraine lacks information systems capable of automating the processes of obtaining the information on the extent of destruction necessary for making operational decisions and of proposing a comprehensive approach to prioritizing the restoration of damaged facilities, taking into account their physical condition, social significance, and historical and cultural value. Most existing solutions are limited to assessing only

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external signs of damage and are unable to provide recommendations on the order of restoration based on a multifactorial analysis.

In light of this, it is particularly important to create an intelligent system that, based on architectural and technical documentation data, building metadata, and using computer vision methods, is capable of determining priorities for the restoration of urban infrastructure facilities. The development and implementation of such a system will not only improve the efficiency of existing resources but also ensure a socially equitable restoration strategy that takes into account community needs, the importance of the facility's functions, and the preservation of national memory.

This work explores the subject area related to the analysis of damage to urban infrastructure and identifies the main problems and challenges that arise during damage assessment and restoration planning. Particular attention is paid to the innovative aspects of the system under development, which is based on the use of computer vision models and deep machine learning for the automated detection of building damage using image data.

Deep learning can, in particular, be effectively used to solve complex tasks: classification, segmentation, and identification of damaged fragments of destroyed building infrastructure. Modern deep learning models are based primarily on the use of convolutional neural networks (CNNs), which allow for improved quality of damage analysis based on the results of computer vision methods and tools. Detecting building damage during military operations and assessing the extent of such damage using intelligent models can ensure effective analysis of the condition of damaged structures and enable prioritized planning for the restoration of these buildings.

The principle of traditional computer vision methods lies in extracting object features from images for subsequent classification. Convolutional neural networks complement the capabilities of computer vision methods through deep learning principles, which ensure the flexibility of neural network models that can be retrained for any possible dataset in tasks involving the identification of defects in damaged buildings [1].

The objective of this work is to develop an intelligent system for the automated detection of damage to buildings based on images, the assessment of the extent of damage, and the prioritization of their restoration, taking into account their cultural and social significance.

2. Literature Review and Problem Statement

The development of systems for the automated detection of building damage in the context of military conflicts, as well as the prioritization of their restoration based on the extent of damage and the cultural and historical significance of the sites, is accompanied by a number of significant challenges. One of the key limitations is the shortage of high-quality annotated data required for effective training of machine learning models. Currently, there is a limited number of publicly available datasets illustrating building damage, particularly as a result of natural disasters. Among these, the xBD dataset [1] is worth highlighting; it contains over 850,000 annotations of buildings on satellite images acquired before and after events (such as hurricanes or earthquakes), with a detailed classification of damage levels. However, the lack of specialized datasets focused on war damage significantly complicates the adaptation of existing methods to the specifics of combat operations and their consequences.

Fig. 1 shows examples of image pairs from the aforementioned dataset.

Models trained on such datasets require paired satellite images (before and after destruction) to effectively analyze damaged objects. This results in significant costs for collecting such data, as well as a reliance on external imaging sources. Moreover, the application of these models may be limited due to the lack of pre-damage historical imagery, which is particularly relevant in the context of military conflicts. The accuracy of models trained on xBD-type datasets is often insufficient when analyzing buildings damaged by combat operations. This is because satellite images do not always capture minor defects (e.g., cracks, localized potholes), and the nature of damage from shelling differs significantly from the effects of natural disasters, which are predominantly represented in existing datasets. The latter focus on global landscape changes, whereas in wartime conditions such changes may be absent or may not correlate with the actual condition of buildings [2]. The overall accuracy of damage assessment depends largely on the quality of the input data. The complexity of analyzing satellite imagery lies in the presence of obstacles, such as neighboring buildings, the surrounding environment, and clouds, which partially or completely obscure the image [3]. Additional factors – shadows, vegetation, adverse weather conditions, smoke, and suboptimal shooting

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angles – also distort visual information, making it difficult to identify key features of objects. Furthermore, the inability to safely collect additional data on-site (due to the threat to experts' lives) limits the ability to expand training datasets to the sizes required for effective model training.

Fig. 1. Landscape samples before (top row) and after (bottom row) the disaster from the xBD dataset

One of the key challenges in developing building damage analysis systems is the need to account for the variety of building materials, such as concrete, brick, or precast concrete, which significantly affect the stability of structures and the feasibility of their restoration [4]. For example, concrete structures are capable of withstanding significant dynamic loads, whereas brick walls demonstrate greater vulnerability to blast waves. Furthermore, the nature of damage in brick and concrete buildings can differ significantly: cracks in brick masonry are often less critical for operational safety than similar defects in concrete structures.

This heterogeneity complicates the creation of unified damage assessment models, as it requires a differentiated approach to analyzing each type of material. An important aspect is the assessment of the condition of load-bearing floors, since damage to them directly affects the overall stability and safety of the building. To detect hidden defects and accurately determine the extent of damage, specialized equipment – such as ultrasonic scanners, laser rangefinders, or ground-penetrating radar – is often required [5]. However, their use is limited due to high costs and the complexity of deployment in wartime conditions. Economic and organizational constraints also play a significant role. Countries affected by armed conflicts often face a shortage of the financial and human resources needed for large-scale infrastructure restoration. In Ukraine, in particular, investment in reconstruction is limited due to the prolonged war [6], which complicates the implementation of high-tech damage assessment methods. Another challenge is the lack of systematic criteria for assessing the cultural and historical value of sites. Uncertainty regarding restoration priorities, stemming from a lack of standardized methodologies and objective indicators, significantly complicates the decision-making process regarding the order of building reconstruction.

Below, we examine existing platforms and software solutions currently used for the automated detection and classification of damage to civil infrastructure objects.

At the start of the full-scale war in 2022, the UN funded the "Infrastructure Semantic Damage Detector" (ISDD) project for Ukraine [7], under which a model was created that uses machine learning algorithms and big data processing methods to analyze infrastructure damage by processing reports. The model uses the open-source ACLED database, which contains global real-world data on the consequences of destruction, as its data source. The system based on this model was developed to determine the location of infrastructure damage and the scale of the resulting losses to enable rapid response. It was also intended to use this system to generate ready-made reports for the purpose of submitting requests for assistance to international humanitarian organizations and calculating the amount of aid required. By analyzing the text of the reports, data on the date, time, location, cause, and type of damage are recorded. One of the challenges addressed by the system's developers is determining the type of damaged infrastructure in the required format. Nine categories were proposed for

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classification: industrial facilities, logistics, energy/power supply, telecommunications, agriculture, healthcare, education, housing, and business. By identifying keywords for each of these categories and using the cosine similarity measure to establish a semantic link between the text of the reports and the infrastructure categories, the system can automatically classify the types of damaged infrastructure.

The final stage of the system's operation is the visualization of the results on an interactive map of Ukraine. The ability to filter the buildings identified and displayed on the map by region and settlement, as well as by their function, allows users to examine the geographic distribution of damage across various types of infrastructure. The ability to generate bar and pie charts allows users to examine the results in greater detail. Figure 2 shows an example of an interactive dashboard built on the ISDD platform. The advantages of the described system include: speed and efficiency; scalability; and the ability to analyze various types of infrastructure.

The disadvantages of this system include: limitations caused by processing only text data without analyzing visual materials; dependence on the quality of text data without the ability to verify the accuracy of the obtained data against data from other sources; the system's focus solely on determining the type of damaged infrastructure and its location, while ignoring the severity of the damage and the assessment of losses.

In 2022, the Kyiv School of Economics, in collaboration with Ukrainian government agencies, initiated the "Russia Will Pay" project, aimed at a comprehensive analysis and assessment of the damage inflicted on the country's infrastructure as a result of military aggression [8]. The project involves collecting and systematizing data from various sources, including official reports from government agencies, business associations, verified media materials, as well as satellite imagery and the results of drone surveys of liberated territories. This approach allows for the assessment of damage not only to buildings but also to critical infrastructure, major roadways, and agricultural land. A key partner in the project is the Polish-American company Tensorflight, which provides satellite imagery of sites free of charge and uses machine learning and artificial intelligence tools to analyze them. The innovation of the method lies in the use of imagery captured at different angles (0° and 30–50° relative to the axis), which makes it possible to assess damage to both roofs and building facades – even if the roof remains intact. After preprocessing the images, they are segmented into undamaged and damaged objects, and the degree of damage is classified – from partial (repairable) to total. Based on historical data on damaged buildings, Tensorflight also provides a preliminary estimate of reconstruction costs. To date, the system has been used to analyze damage in cities such as Bucha, Irpin, and Mariupol. Additionally, the project helps prioritize sites for restoration by providing analytical support for decision-making.

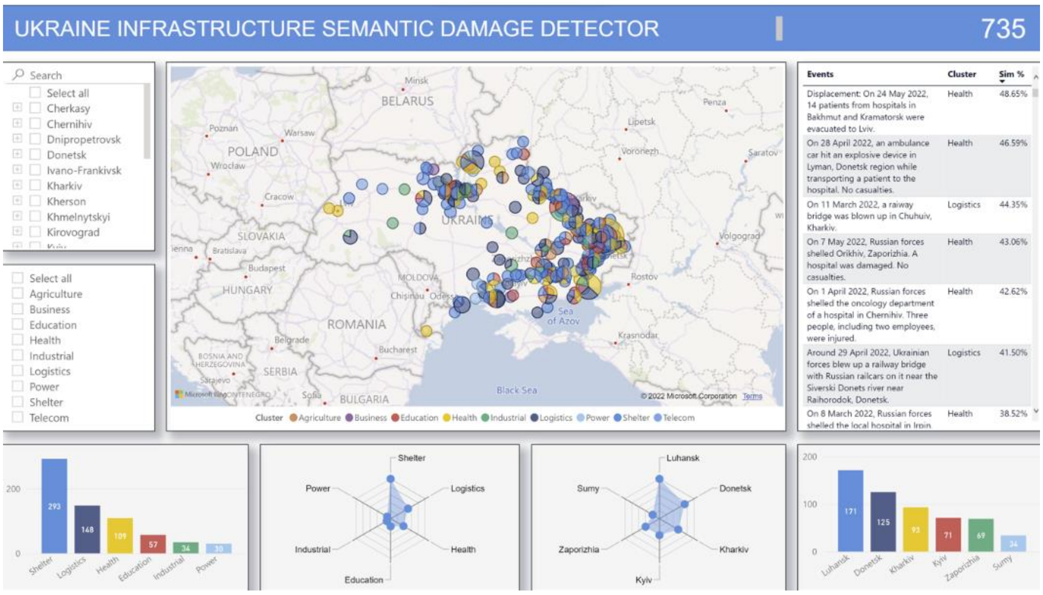

Fig. 2. Example of an interactive board built using the "Infrastructure Semantic Damage Detector" platform

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The system offers the following advantages: a multimodal approach to gathering information about damage; detection of damage to building facades with intact roofs using the proposed satellite imaging approach. The disadvantages of the system under consideration include: the dependence of users (government agencies) on a commercial company from another country; the possibility of confidential information about infrastructure facilities being leaked; and the high cost of collecting and processing satellite data.

One of the leading commercial companies specializing in assessing damage to buildings caused by external factors is FlyPix AI [9]. The company has developed a geospatial analytics platform (Geospatial AI platform) that integrates pre-trained machine learning and deep learning models, as well as artificial intelligence tools for processing drone imagery, aerial photography, and high-quality satellite images. The platform provides automated detection, segmentation, and classification of building damage in real time. Initially, FlyPix AI's models were focused on analyzing damage caused by natural disasters and were successfully used to assess damage to settlements following earthquakes in Turkey and Japan. In 2025, the company adapted its solutions to analyze building damage resulting from military operations in Ukraine. The official website notes that previously developed models, trained on natural disaster data, did not provide sufficient accuracy for military damage. Therefore, new models were created, trained on specialized custom datasets containing information about destruction in combat conditions. To improve accuracy, multimodal data fusion was also implemented.

The Geospatial AI Platform features machine learning and deep learning models with various architectures for the segmentation and classification of images of damaged buildings (specifically, U-Net and Mask R-CNN deep learning models combined with trained ResNet34, SeResNext50, Inception v3, and EfficientNet B4 models). The highest accuracy was achieved by using an ensemble of Mask R-CNN models (for detecting damaged structures) and Inception v3 models (for assessing the degree of damage). After the selected deep learning models have completed their tasks, the system allows users to work with dashboards and interactive maps to examine the results in greater detail. The advantages of the described system include: a wide selection of models with different architectural types, with the ability to fine-tune them on user-provided datasets to solve a wide range of diverse tasks; convenient tools for automated image annotation in the user dataset; multifunctionality; no requirement for users to possess knowledge or skills in machine learning and artificial intelligence to use the system; integration of the configured model into cloud environments; real-time analysis of satellite and drone imagery. The system's drawbacks include: limited capacity for building monitoring and free usage based on the number of requests; the inability for users to view detailed information about detected damage; lack of information regarding the type of structure being inspected; and the inability to prioritize building restoration based on their cultural and social value.

Another platform for analyzing building damage is the "AI Damage Detector" platform from T2D2 [10]. This cloud-based platform allows for the detection and classification of damage to buildings using computer vision algorithms (Fig. 3). It should be noted that T2D2 did not aim to assess damage to structures caused by military actions, but rather focused on detecting various types of damage on facades during building condition monitoring, which may partially relate to the topic of this study.

Platform users can use images and videos captured from mobile devices, cameras, or drones as input data for the models they build. The system built on this platform allows users to track the deterioration of buildings over time by comparing images and videos taken at different intervals. The "Inspection Cloud" cloud environment developed by T2D2 allows users to store necessary materials and integrates with Google Drive, OneDrive, and Box. Advantages of this system: the ability to generate detailed reports describing various types of damage found; high classification accuracy due to large proprietary training datasets used to train the proposed models. The system's drawbacks include: the lack of a free plan (with the exception of a two-week trial period); a lack of focus on identifying specific damage sustained by buildings during military operations; lack of assessment of the socio-cultural significance of buildings; lack of assistance in making decisions regarding the restoration of structures as well as determining the order of building restoration.

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Fig. 3. Interface of the "AI Damage Detector" platform

At the start of the war, various volunteer organizations launched several projects aimed at documenting building damage by creating 3D models. These projects cover both simple structures and those of cultural or historical value. Drones and aerial photography are typically used to survey structures, and 3D models are created using photogrammetry. The results obtained allow not only for documenting damage but also for specialists to use them for further analysis and planning of restoration work. Among the most well-known projects in this field is the "War up Close" project, which uses 360° panoramic photographs, drone footage, and 3D modeling to document the criminal destruction of Ukraine’s infrastructure for subsequent presentation to the global community [11]. Fig. 4 shows one of the pages of the War in 3D project featuring constructed 3D models.

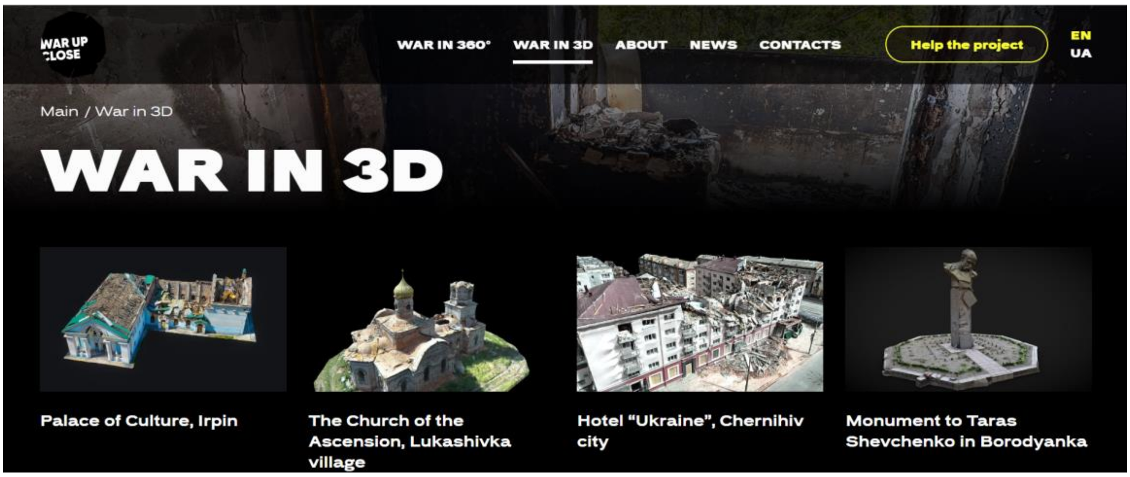

Fig. 4. Example of a page from the "War in 3D" section of the "War up Close" project

The project team is actively collaborating with various government agencies and helping rescue workers clear debris and assess the true extent of the damage.

The global initiative for Ukraine’s recovery, UNITED24, has launched a joint project with the IT company LUN, using an app with patented technology that builds 3D models of structures based on drone imagery [12]. This initiative allows for tracking the progress of the reconstruction of damaged buildings and raises funds for infrastructure restoration. Currently, the program is limited to Kyiv and covers 17 sites. Figure 5 shows an interactive map of Kyiv with the locations of damaged buildings.

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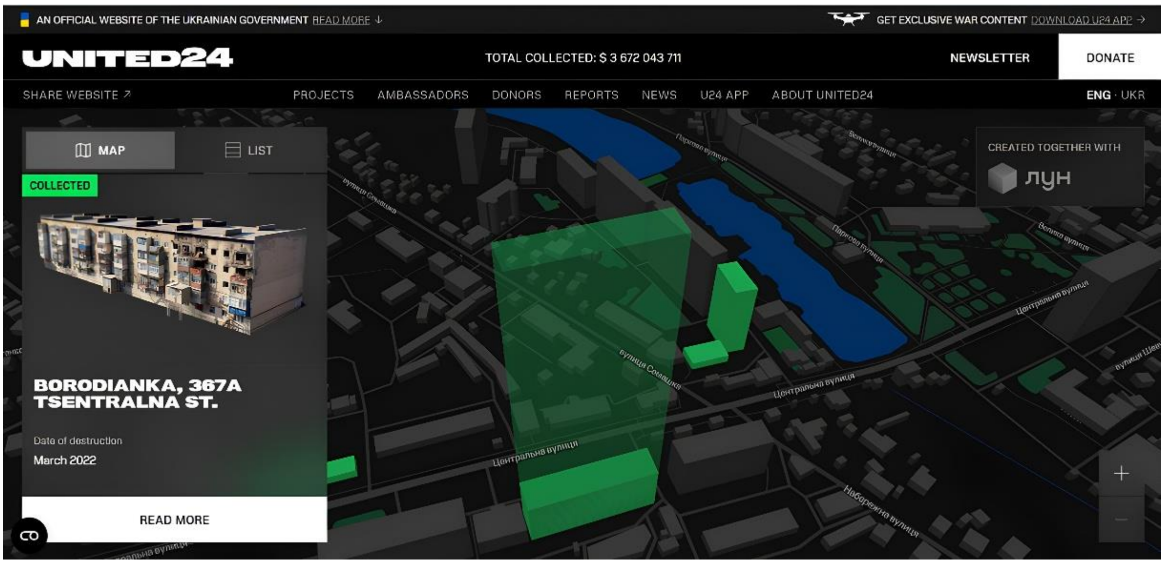

Fig. 5. Example of an interactive map showing the locations of damaged buildings, provided by UNITED24

Unlike previous initiatives, which have focused more on ordinary residential buildings, the volunteer initiative Scan UA works with Ukrainian heritage sites that have been damaged or are at risk of disappearing [13]. The goal of this initiative is to create a digital archive of Ukrainian heritage to preserve the memory of cultural heritage, as well as to provide information about the damage inflicted on the country's architecture. Figure 6 shows a 3D model of the damaged Fire Station No. 4 in Kharkiv.

The advantages of all the initiatives described are that the 3D models produced as a result of their work allow specialists to examine the damage present on the buildings in greater detail and plan restoration work more thoroughly. At the same time, a significant drawback is the lack of an automated mechanism for detecting damage and determining the level of destruction of buildings. These initiatives do not propose an objective mechanism for selecting buildings for structural damage assessment or for determining the order of restoration work.

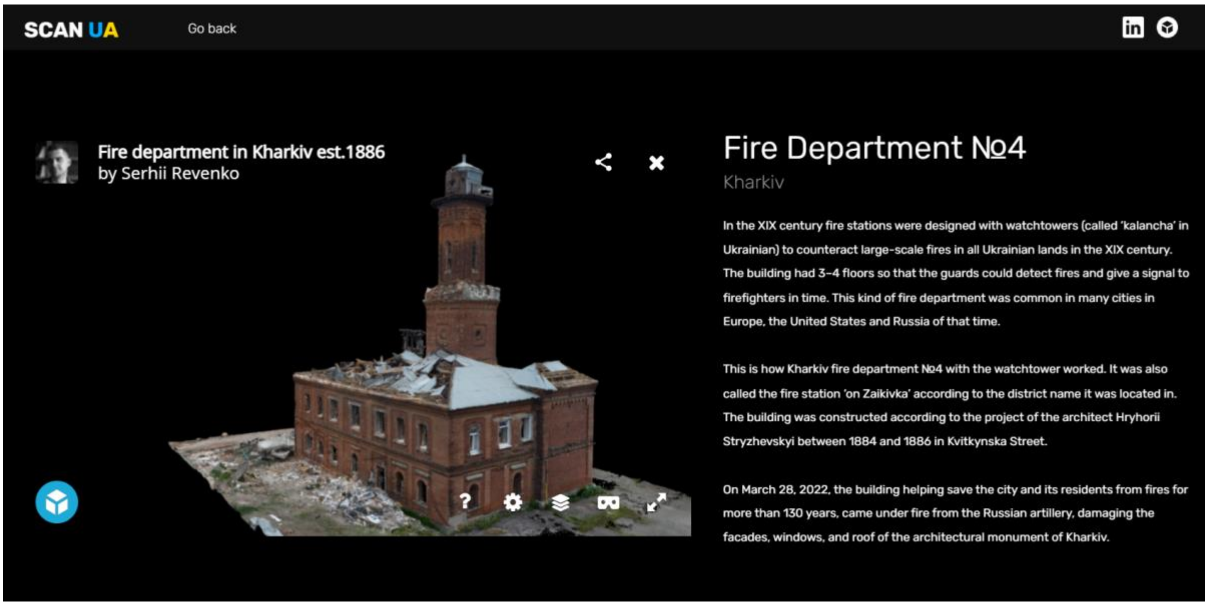

Fig. 6. Interface page showing a 3D model of the damaged Fire Station No. 4 in Kharkiv

Below we present the results of scientific studies most relevant to the topic of this paper.

In [14], the authors proposed an approach to the automated detection of damaged buildings in satellite and

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aerial imagery, based on unsupervised machine learning methods. Images of Ukrainian cities from Google Earth, obtained before and after the start of the war, were used as input data. Before applying machine learning algorithms, the images underwent preprocessing, which included georeferencing, orthorectification, contrast enhancement, and brightness equalization. The algorithm consisted of three main stages. In the first stage, Principal Component Analysis (PCA) was applied to determine the principal components describing the directions of maximum data variance. In the second stage, the K-means algorithm was used to partition the image into clusters by grouping similar areas of change. In the final stage, the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) clustering method was applied to identify dense regions corresponding to damage. The result of the algorithm's operation was a binary damage mask, where damaged areas were highlighted for further analysis. The advantages of the proposed method lie in its high damage detection accuracy (Accuracy = 98.13%, F1 Score = 70.90%), as well as its ability to work with data of varying quality and spatial resolution without the need for pre-training complex deep learning models. However, the algorithm has certain limitations. First, it does not accurately define the boundaries of different types of damage. Second, the presence of visual artifacts, such as shadows, glare, or uneven lighting, can significantly reduce the accuracy of the results. Furthermore, the effective application of the method requires the availability of satellite or aerial images taken before and after the damage, which are not always obtainable. Additionally, not all types of damage are clearly visible from above, which limits its scope of application.

In [15], an innovative approach to determining the degree of building damage was proposed, based on the construction of a Damage Detection Map (DDM) model. Photographs of damaged buildings obtained after the earthquakes in Nepal and Ecuador, Typhoon Rui, and Hurricane Matthew were used to train the model. A distinctive feature of this approach is that the images were captured at ground level, which allows the model to be used in the future to analyze photographs posted on social media by ordinary users without the need for specialized equipment.

The model's architecture is based on a convolutional neural network (CNN), specifically a modified VGG19 model, whose outer layers were fine-tuned on collected and labeled datasets. To visualize and interpret the results, the Grad-CAM method is applied in the final convolutional layer, which calculates weights based on gradients for each object map, highlighting the most significant areas. This allows for the generation of a DDM heatmap, where areas of high intensity correspond to detected damage. To classify the severity of damage (minor, moderate, severe), the authors proposed the DAV (Damage Assessment Value) metric, which is calculated as the average of the intensities on the heatmap. The higher the DAV value, the more severe the damage. Using DAV thresholds allows the model to be adapted to different types of damage, providing flexibility in determining their severity. The model's output is a thermal map highlighting the damage, as well as a classification of the building by damage severity. This approach opens up possibilities for automated analysis of photographs taken by non-specialists, significantly expanding the capabilities for documenting and assessing damage in real time.

The main advantages of the proposed approach [15] are its cost-effectiveness and ability to be deployed immediately following the occurrence of emergencies. This is particularly relevant in situations where large volumes of data can be rapidly collected from social media, enabling a prompt response to damage without the need for specialized equipment. Another important advantage is the clarity and comprehensibility of the results, which helps build trust in automated systems for detecting and classifying the extent of damage to buildings.

In a subsequent study [16], the authors expand on this approach, emphasizing the advantages of the Grad-CAM and Grad-CAM++ methods, which provide improved interpretability of results. Additionally, the application of the model for classifying damage to various types of infrastructure – including roads, bridges, and buildings – is demonstrated, broadening its scope of practical use. However, the method has certain limitations. First, small-scale damage may not be visible on heatmaps, creating a risk that it will be overlooked during the planning of restoration work. Second, although the method effectively visualizes large-scale damage, its capabilities are limited when it comes to detecting minor defects. At the same time, the algorithm for automatically assessing the severity of damage allows buildings to be classified by degree of damage, which is an important advantage for prioritizing restoration efforts.

In [17], a method was proposed that allows for the assessment of the degree of building damage on a scale from 0 to 1 based solely on aerial imagery, without the need for before-and-after photographs of the structures.

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To train the model, a custom dataset was created, comprising 250 images of buildings damaged by natural disasters, collected from open sources and pre-annotated by experts. The method's architecture involves three parallel feature processing streams, whose results are combined for the final damage severity prediction. The first stream processes unprocessed color images using a VGG-based convolutional neural network to extract deep features. The second stream first applies semantic segmentation using DilatedNet to remove extraneous objects and extract only relevant elements (e.g., building walls), and then processes the resulting color mask in a manner similar to the first stream. The third pipeline converts the segmented image into a binary mask representing the building's contours with damaged areas and analyzes it using a simplified LeNet architecture. The features obtained from all three streams are combined into a single vector, which is processed by a fully connected layer with a sigmoid activation function to determine the building's damage level as a continuous value. The advantages of the proposed approach lie in the absence of a need for data on the condition of objects prior to destruction, as well as in the ability to obtain a continuous assessment of the degree of damage, which allows for the flexible prioritization of the restoration of structures with different types of damage. However, the method also has significant limitations. First, the high computational complexity requires substantial resources for model training. Second, the quality of the results depends on the training dataset, which must be pre-annotated by experts. Discrepancies in assessments by different groups of experts or changes in the criteria for determining the severity of damage may necessitate the preparation of a new dataset and retraining of the model, which complicates its practical application.

In [18], an approach was proposed aimed at reducing the computational complexity of models by utilizing computer vision methods that account for the building materials used during construction. The data source for the experimental studies was a custom Google My Maps map created in April 2022, which contains images of damaged buildings in Mariupol taken from both ground-level and drone perspectives. Image annotation was performed on the Roboflow platform using four damage severity classes adapted from the EMS-98 classification. Various augmentation methods were applied to expand the training dataset and improve model robustness. A pre-trained YOLOv8 model was used to automatically determine the damage level; its training lasted 50 epochs and yielded the following results: mean average precision (mAP) was 58.4%, precision was 64.1%, and recall was 52.5%. The same architecture was used to determine the type of development project. The main advantage of this approach is the use of open data collected by eyewitnesses to the events. The images used to train the model vary in quality, distance to the object, and shooting angles, which contributes to the model's stability when working with new data. In addition, the use of the modern universal YOLOv8 model allows for a balance between prediction accuracy and productivity. However, the method has certain limitations. First, the classification of damage severity is based on a five-point scale for assessing post-earthquake damage, which may not fully correspond to the nature of damage caused by military actions, potentially affecting the model's accuracy. Second, the subjectivity of assigning structures to different classes can lead to ambiguities in classification results, complicating the interpretation of the obtained data.

In [19], an approach was proposed that addresses these issues using a simplified version of the YOLOv5 model, optimized for real-time operation with minimal computational cost while maintaining high accuracy. To train and test the model, a specialized dataset titled "Ground-level Detection in Building Damage Assessment" was created, comprising ground-level photographs of damaged buildings with detailed annotations of various types of damage. The model was trained to recognize damage types such as collapses, cracks, material delamination, and debris accumulation. The modification of the base YOLOv5 architecture, named LA-YOLOv5, involved the introduction of Ghost Bottleneck elements and the CBAM (Convolutional Block Attention Module), as well as improvements in handling objects of different scales. These changes allowed the model to maintain high accuracy while significantly reducing the memory requirements for its deployment. The main advantage of the proposed approach is its high processing speed, making the model suitable for use in situations that require rapid damage detection and quick response. In addition, the model's ability to recognize different types of damage allows for a more in-depth analysis of the damage, which facilitates informed decision-making regarding the priorities of restoration work.

However, the method has a significant limitation – the lack of a formalized algorithm for assessing the degree of building damage, which complicates the automated determination of the level of damage and may require additional expert assessment for accurate classification of objects.

The main drawback of the methods discussed above is the lack of an objective approach to assessing the degree of building damage and the ability to adapt this method to various situations requiring the application of the developed models. Recently, a number of studies have appeared dedicated to solving the problem of determining the priority of restoring one structure over another. For example, Article [20] describes the application of the Multi-Criteria Decision Analysis (MCDA) method to determine priority infrastructure objects for construction or reconstruction under limited financial resources, consisting of a combination of the two-phase AHP method and the TOPSIS method. To determine the weights of the selected criteria, the AHP method was used, which in the first phase assigns weights to the criteria taking into account the opinions of all stakeholders, and in the second phase adjusts the determined weights based on the decision of the lead expert (key person). Next, the priority for each object is calculated using the TOPSIS method by ranking the objects according to their proximity to the ideal object. The advantages of this approach include the transparency of the ranking process and the ability to account for different perspectives on the task at hand. Its disadvantages include both the time and computational complexity of configuring the AHP method when considering multiple criteria with the participation of a large number of experts.

In [21], a comprehensive approach was implemented to determine the order of implementation for proposed disaster recovery projects, where a set of comparison criteria was selected for each project. The Best Worst Method (BWM) was used to determine the importance of each criterion, allowing experts to select the most and least important criteria for the projects and, based on their comparisons, calculate weights for the entire evaluation system. The TOPSIS, ELECTRE III, VIKOR, and PROMETHEE methods were applied for ranking. The final result (a ranked list of projects) was obtained by linearly combining the results provided by each of the ranking methods into a single priority vector while minimizing discrepancies. To verify the reliability of the results, an ANN neural network trained on historical data about completed projects was used. The results obtained using the MCDA method coincide with the neural network's predictions. The advantages of the described approach include the hybrid use of four ranking methods, which allowed for more accurate results, and the BWM method for determining criterion weights, which is less labor-intensive compared to the AHP method but also ensures high consistency of decisions.

Let us now consider the problem of applying computer vision tools, which are to be used in conjunction with deep learning methods to implement the tasks set in this study. In the context of the task of detecting damage to buildings during wartime and assessing the extent of such damage, it is necessary to select a computer vision method capable of effectively detecting and analyzing damage in input images. To solve this problem, approaches such as image classification, object detection, semantic segmentation, and instance segmentation can be applied [22, 23]. One of the fundamental areas of computer vision is image classification, which involves assigning an image to one or more categories based on its visual characteristics [24]. Classification models are trained on a dataset of pre-labeled images, where each image must correspond to a specific class. In the context of this work, these may be images with text labels ("damaged building", "partially damaged", or "undamaged") or numerical values (degrees of building damage). There are a number of pre-trained classification models (e.g., ResNet or VGG) that require minimal fine-tuning to achieve high accuracy and image processing speed [25]. At the same time, these models are typically unable to determine the location or boundaries of damage, which significantly limits their usefulness for tasks requiring the localization of urban infrastructure objects. Furthermore, they require the involvement of experts for data annotation, which can lead to subjectivity in assessments, as different specialists may interpret the extent of building damage differently during visual analysis. This creates a risk of label inconsistency, which negatively impacts the model's reliability. It is advisable to focus on computer vision methods that enable the localization and detailed analysis of damage, allowing the process of assessing the extent of destruction to be separated from the model and carried over to the next stage.

An important area of computer vision is object detection, which focuses on identifying and localizing objects in an image by creating bounding boxes around them, followed by classification. During the detection process, the model learns to recognize objects based on their visual characteristics, such as shape, texture, or color, and to create rectangular bounding boxes that enclose these objects, along with labels indicating their class [26]. In this process, detection identifies objects as separate units but does not provide information about their exact boundaries. The main advantage of this approach is that it allows for the precise determination of an object's location within an image, which represents significant progress compared to image classification. However, its drawbacks are that the bounding boxes do not reflect the exact shape or boundaries of the objects, which reduces the accuracy of analysis in tasks requiring detailed information about the structure of damage. In cases where objects overlap, have blurred boundaries, or are closely spaced, this approach may lose accuracy, as the bounding boxes may incorrectly enclose objects or miss them [27].

To achieve the highest efficiency in detecting building damage, it is worth considering the field of image segmentation, which allows not only determining the location of objects but also their exact contours. There are two main types of image segmentation: semantic segmentation and instance segmentation [28].

Semantic segmentation involves classifying each pixel in an image, determining its membership in a specific class. A distinctive feature of this approach is that individual instances of the same class are not distinguished but are treated as a single category. Because the method provides a detailed analysis of the image at the pixel level, it becomes possible to accurately estimate the area and distribution of objects in the image. Additionally, semantic segmentation performs well when analyzing images with a large number of objects or complex structures, where segmentation of the entire scene is required. At the same time, the fact that semantic segmentation yields detailed information about objects and their clear boundaries is a drawback of this approach, as it does not allow for distinguishing individual instances of the same class, which limits its use in tasks requiring the identification of individual objects. For the task at hand, using semantic segmentation allows us to estimate the total area of damage, but it cannot provide information about the number or shape of individual instances of a single type of damage.

This limitation can be addressed by instance segmentation, which combines the capabilities of object detection and semantic segmentation, enabling the identification, localization, and pixel-level classification of individual object instances in an image. This method not only determines the category of objects but also creates separate pixel masks for each instance, allowing for the clear separation of different objects within the same class. The advantages of this approach include the ability to perform a comprehensive, detailed analysis of images containing a large number of objects or complex structures, providing information on all detected elements. A drawback of this approach is the need for significant computational resources.

Therefore, for the task of detecting damage to buildings, the best approach is to use instance segmentation, which allows not only for the detection of damage but also for the precise determination of its boundaries and quantity, which is important for a comprehensive assessment of the scale of destruction and the planning of restoration measures.

3. Purpose and Objectives of the Study

Based on the results of the analysis presented above, we formulate the purpose and objectives of this work.

The objective is to develop an intelligent system for the automated analysis of damage to urban infrastructure objects, which would enable the effective processing of large volumes of images obtained using computer vision techniques, for the subsequent assessment of the level of damage and decision-making regarding the priority of their restoration.

To achieve this goal, the following must be carried out:

– selection of computer vision models for segmenting instances of the analyzed image sets of damaged objects;

– balanced formation of datasets containing images of buildings with various types of damage;

– ranking of damaged urban infrastructure objects to determine the priority of their restoration;

– definition of the structure and functions of the proposed intelligent system for automated damage analysis;

– software implementation of the main modules of the proposed system;

– implementation of the server-side and system interface;

– experimental research and testing of the system.

4. Materials and Methods

4.1. Selection of computer vision models for segmenting instances in the analyzed image sets

Instance segmentation is an effective approach for solving the problem of detecting war-induced damage to buildings, where a single image may contain 10 to 100 small instances of damage with a significant

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class imbalance. After determining the field of computer vision, it becomes important to correctly select a model from this field that is capable of accurately identifying all damage and operating at high speed. This section is devoted to a review of modern computer vision models for instance segmentation, with an explanation of their suitability for solving the given task.

Currently, there is no consensus on the best object segmentation model, given the variety of comparison criteria: segmentation accuracy, processing speed, computational efficiency, and adaptability to class imbalance [29]. It is advisable to compare segmentation models based on mAP scores for bounding boxes, masks, and ease of configuration. In terms of speed, models from the YOLO family have a significant advantage; their latest versions have the following mAP values: 54.7 for bounding boxes and 43.8 for masks [30]. Among the models that are slower but provide high object detection accuracy and attention to small details, the modern architectures of BEiT3, Mask2Former, MaskDINO, and OneFormer are worth noting. However, a significant drawback of these models, which complicates their practical use, is their high computational complexity. In addition, these models require large amounts of finely annotated data for fine-tuning.

Other relevant segmentation models include Mask R-CNN, Panoptic FPN, and YOLACT++. Mask R-CNN provides accurate pixel-level segmentation and is suitable for tasks requiring maximum accuracy, such as visualizing sections of damaged buildings. Panoptic FPN combines instance segmentation and semantic segmentation, providing a comprehensive understanding of the scene. YOLACT++ is designed for fast, real-time object segmentation, which is useful for video analysis, action recognition, and object counting. The advantages of each model should be considered based on the challenges encountered in each specific application of computer vision for segmentation.

In particular, for the task of detecting building damage among the models considered, special attention should be paid to the latest models in the YOLO and Mask R-CNN families, as the former are capable of combining high image processing speed with good accuracy, while the latter remain leaders in tasks where maximum pixel segmentation accuracy and detail are critical.

The YOLOv11 and Mask R-CNN models represent two different approaches to solving the object segmentation problem, each with its own architectural features, advantages, and limitations.

The YOLOv11 model implements a modern single-stage algorithm for object segmentation tasks, built on the YOLO family architecture, which was originally developed for fast and efficient object detection in images and later adapted for segmentation tasks [31]. The basic principle of such models is to divide the image into a grid and simultaneously predict bounding boxes, object classes, and segmentation masks for each region within a single pass through the image [31]. The YOLOv11 architecture features an improved backbone based on Darknet-53, which ensures effective feature extraction using convolutional layers. The model employs a modified C2F module, which improves the quality of fine-scale feature extraction and reduces the size of convolutional filters from 6×6 to 3×3, thereby lowering computational costs. A significant feature is the use of a decoupled head (decoupled head), which separates the tasks of coordinate regression and classification, improving segmentation productivity and accuracy.

To improve the stability and quality of predictions during segmentation, the Pseudo Ensemble method is often used, allowing the results of several models to be combined for a more stable outcome. These architectural solutions make YOLOv11 a very fast and efficient model capable of processing up to 128 frames per second, which is particularly important for real-time applications and systems with limited resources.

The main advantages of YOLOv11 are its high data processing speed and balanced accuracy. However, despite its improved architecture, this model may exhibit reduced accuracy compared to two-stage methods, especially when dealing with complex or small objects.

In contrast to YOLOv11, Mask R-CNN is a two-stage model that has gained widespread recognition due to its high object segmentation accuracy [32]. The Mask R-CNN architecture includes a backbone network (typically ResNet-50 or ResNet-101 with FPN), which extracts multi-level features from the image. Next, the Region Proposal Network (RPN) generates region proposals, which are precisely aligned using the RoI Align layer to extract features of specific regions of interest.

The scaled features are fed into the model’s head, which concurrently performs object classification, bounding box regression, and the generation of pixel-level segmentation masks for each object. Model training is based on a combined loss function that accounts for all three of these tasks. A key feature of Mask R-CNN is its high-quality pixel-level segmentation and robustness to challenging image conditions, making it highly sought

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after for applications that require precise object detection. The main drawback of Mask R-CNN is its relatively high computational complexity and slow inference time, which limits the model's use under strict time constraints.

Thus, the YOLOv11 and Mask R-CNN models implement different approaches to image segmentation and are effective for use in automated defect analysis systems for damaged urban infrastructure objects. YOLOv11 provides higher processing speed and generally better accuracy compared to Mask R-CNN. At the same time, Mask R-CNN remains the leader in tasks requiring the most accurate and detailed object segmentation, despite its significant computational load. The choice of model should be based on the requirements of the specific task and the available computational resources.

4.2. Addressing the Issue of Class Imbalance in the Training Image Dataset

In the process of developing an automated system for detecting damage to buildings during military operations in Ukraine, a significant problem arises due to the uneven distribution of classes in the training dataset. The class imbalance is caused by the natural heterogeneity of the types of damage observed in the images. In particular, some categories of damage (e.g., broken windows) are significantly more common due to their high frequency of occurrence. For example, even in the absence of a direct hit on a building, the blast wave often causes damage to windows, which significantly increases the proportion of such objects in the dataset. At the same time, buildings with critical damage, such as collapsed structures, usually also have broken windows, which further increases the number of instances in this class. Since there are numerous windows in every building, the number of instances in this class significantly exceeds other damage categories, such as cracks or collapsed walls.

This uneven distribution of data creates conditions for the model to be biased toward the dominant class. When using standard training approaches, the model will demonstrate high overall accuracy, since most annotations in the dataset belong to the dominant class, and their correct classification ensures a high accuracy score. However, when the model is used in practice, its effectiveness will be significantly reduced, as such a model will be unable to detect underrepresented but critically important classes that are crucial for assessing the extent of damage and planning reconstruction. Thus, in this case, high overall accuracy does not reflect the model's actual ability to solve the given task, which reduces its practical value. Class imbalance issues should be taken into account both for preprocessing the dataset and for tuning computer vision methods. One of the basic and effective methods for addressing class imbalance through preprocessing of image datasets in computer vision tasks is data augmentation, which allows not only for increasing the total size of the training sample but also for balancing the representation of minority classes by varying the structure and appearance of images.

All image augmentation methods can be broadly divided into basic and advanced [33]. The basic approach combines methods of geometric and non-geometric image manipulation, as well as image erasure techniques. Geometric transformations, whose main operations are rotation, translation, scaling, axis translation, and angle translation, change the spatial position of objects, allowing for increased model invariance to the orientation and position of objects. On the one hand, such transformations allow for increased model robustness, given that in reality, damage may be captured from different camera angles or in different positions. On the other hand, transformations that radically alter the spatial arrangement of objects in the frame can lead to the creation of training images that do not occur in reality and may negatively impact the model, resulting not merely in a lack of improvement in accuracy but in a significant deterioration in quality. In general, the selection and use of each geometric transformation method requires a comprehensive preliminary check to ensure that the resulting images correspond to reality. Non-geometric transformation methods include changes in color space, brightness, and contrast, as well as noise injection and filtering, which improve the model's robustness to variations in lighting and textural noise. Unlike geometric transformations, this approach is safer to use and does not have such a strong impact on reducing the model's prediction accuracy. Using this approach to data augmentation makes the model more robust to cases where images were captured under different shooting conditions (using different devices and with varying image quality). However, it is important not to overuse these methods, as this can lead to a significant deterioration in image quality and the model's inability to distinguish between the desired classes during training. Erasing methods (specifically CutOut, Random Erasing, and GridMask) involve the deliberate removal of random or regular sections of the image, which forces the model to pay more attention to different parts of the object rather than just the most prominent features, thereby facilitating better recognition of rare or inconspicuous objects.

Advanced image augmentation techniques include image mixing methods (such as Mixup, CutMix, SaliencyMix, and PuzzleMix), which create synthetic images by combining regions from two or more images, while proportionally combining labels, as well as self-learning-based methods (in particular, AutoAugment and Fast AutoAugment), which are capable of automatically selecting optimal augmentation strategies.

In the analyzed images of buildings with severe damage sustained during combat operations, significant destruction of building parts and minor damage (e.g., broken or destroyed window frames) are typically present. It turns out that minor classes (collapsed structures, cracks, plaster debris) and major classes (broken windows) are neighbors in the same frames, and simply multiplying the number of input images only proportionally increases the proportion of both types of objects without changing their relative balance. With limited tools, for example, when using the basic Roboflow plan, this problem can be solved through region-selective transformations [33]. First, targeted cropping allows us to extract individual fragments from the input images that are concentrated on minor classes. In this case, the cropped areas containing cracks or debris become independent instances, which increases their frequency in the training sample and enhances the contribution of the corresponding gradients during optimization. Given the presence of both minor and major classes in a single image, as well as certain limitations of augmentation approaches on Roboflow, it is advisable to consider addressing the class imbalance problem using other approaches. To this end, one can use a Weighted Dataloader [34], which works by adjusting the probability of selecting samples when forming training batches: elements of rare classes are assigned higher w eights, increasing their frequency of appearance during training. The key advantages of this approach are its ease of use and versatility, as it requires no modification of the model architecture and affects only the data selection strategy. A more complex but more effective approach to addressing class imbalance is the two-phase learning approach, in which the model is first trained on a balanced subsample and then fine-tuned on the full, unbalanced dataset. In the first stage, methods such as Random Under Sampling and minority class augmentation are used to create a more balanced sample, allowing the model to effectively learn to recognize rare objects. Afterward, the model is fine-tuned on the full dataset with the natural class distribution to adjust predictions based on real-world statistics and improve generalization ability. The advantage of this approach is the ability to focus on rare classes without losing information about the actual distribution. The method is versatile and easily combines with techniques for addressing class imbalance that use specialized loss functions. The main drawbacks of this approach are its increased computational time and resource requirements, which stem from training the model twice on different subsets. Overall, despite this limitation, two-phase training remains an effective and widely used approach for improving model quality in tasks with significant class imbalance.

4.3. Ranking Damaged Urban Infrastructure Objects to Determine the Priority of Their Restoration

Determining the priority of restoring damaged urban infrastructure objects requires the use of ranking methods that ensure an objective ordering of structures based on various multiple criteria. In modern research, MCDM and LTR methods are used to solve such problems, as they allow for the integration of heterogeneous data and the optimization of the decision-making process. Both approaches are applied in practical planning tasks but differ in terms of input data, implementation complexity, scalability, and the level of transparency of the results. To analyze them, we will consider the most commonly used MCDM and LTR algorithms.

MCDM methods are widely used in urban infrastructure planning, environmental science, and strategic analysis. Their main advantage is the ability to formally account for heterogeneous evaluations (quantitative and qualitative), as well as ease of implementation without the need for prior model training [35]. One of the most common methods in this group of algorithms is the TOPSIS algorithm [36]. This method involves selecting the alternative that is closest to the hypothetically best solution and, at the same time, farthest from the hypothetically worst solution. If the input data consists of m alternatives and n criteria, then the first step is to construct a decision matrix containing the value of each criterion j for each alternative i.

$$X = \left[x_{ij} \right], \tag{1}$$

where $i = 1,\ldots,m$; $j = 1,\ldots,n$.

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The next step in the algorithm involves creating a matrix of normalized values $R=\left[r_{ij}\right]$ by normalizing the decision matrix constructed in the previous step, in order to eliminate the influence of different units of measurement on the prioritization process:

$$r_{ij} = x_{ij} \Big/ \sqrt{\sum\nolimits_{i=1}^{m} x_{ij}^2} . \qquad (2)$$

To account for the relative importance of each criterion for the elements of the normalized matrix obtained in the previous step, criterion weights w_j are applied. In the current step, a weighted normalized matrix is formed:

$$V = \left[v_{ij}\right], \qquad (3)$$

where $v_{ij} = w_j \times r_{ij}$; w_j – the weight value of the j-th criterion; r_{ij} – the normalized value of the j-th criterion for the i-th alternative.

Next, the best and worst decisions are identified by determining the corresponding value for each criterion.

$$A^+ = \left\{v_1^+, \ldots, v_n^+\right\}, \qquad (4)$$

$$A^- = \left\{v_1^-, \ldots, v_n^-\right\}, \qquad (5)$$

where $v_j^+ = \max\limits_{i} v_{ij}$ – the best value of the criterion; $v_j^- = \min\limits_{i} v_{ij}$ – the worst value of the criterion.

At this stage, the preparatory steps are completed and the ranking process itself begins. For each alternative, the Euclidean distances to the predefined ideal and anti-ideal points are calculated.

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2}, \qquad (6)$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2}, \qquad (7)$$

where D_i^+ – the distance from alternative i to the optimal solution; D_i^- – the distance from alternative i to the anti-ideal solution.

The algorithm concludes by calculating, for each alternative, the relative proximity coefficient to the optimal solution C_i:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-},\ 0 \le C_i \le 1. \qquad (8)$$

It is generally accepted that the higher the value obtained, the closer the alternative is to the ideal. Therefore, the best alternative is the one with the highest relative proximity coefficient. The result of this algorithm is a priority list containing alternatives ranked in descending order of their relative proximity coefficients.

Another widely used MCDM method is the AHP algorithm, which is used to structure complex problems and rank alternatives based on multiple criteria. The AHP method is based on decomposing the decision-making problem into a hierarchical structure consisting of an objective, criteria, subcriteria, and alternatives [35]. The basic algorithm of this method is implemented sequentially in several steps. In the first step, a pairwise comparison matrix is formed based on the results of expert surveys $A=\left[a_{ij}\right]$, in which each element reflects the relative importance of criterion i compared to criterion j. When constructing such a matrix, the principles of reciprocity and self-comparison are taken into account. The next step involves forming a vector of normalized weights as the principal eigenvector of matrix A.

$$Aw = \lambda_{\max} w, \qquad (9)$$

$$\lambda_{\max} \ge n, \qquad (10)$$

where $\lambda_{\max}$ – is the largest eigenvalue of the matrix A; w – normalized main eigenvector; n – number of criteria.

To determine the normalized weight vector, it is important to first calculate the largest eigenvalue $\lambda_{\max}$:

$$\lambda_{\max} = \frac{\sum a_j w_j - n}{w_j} . \qquad (11)$$

To calculate the vector w it is also possible to use the method of power products:

$$w = \lim_{k\to\infty} \frac{A^k e}{e^T A^k e}, \quad \text{where} \quad e = \left(1,1,\ldots,1\right)^T . \qquad (12)$$

To verify the algorithm's results and the consistency of pairwise comparisons, the consistency index CI and the consistency ratio CR are calculated:

$$CI = \frac{\lambda_{\max} - n}{n-1}, \qquad (13)$$

$$CR = CI/RI , \qquad (14)$$

where RI – the average consistency index of a random matrix of size $n \times n$.

The AHP method yields a vector of criterion weights that reflects the relative importance of each criterion in the decision-making process, the values of the alternatives' global priorities, and a ranked list of alternatives in order of priority from highest to lowest, based on the calculated global priorities.

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The AHP method has both advantages and disadvantages [35]. Its advantages include: flexibility, stemming from the AHP method's ability to easily adapt to multi-criteria analysis tasks, taking into account both quantitative and qualitative criteria; support for collective expert participation in decision-making by calculating the geometric mean of individual pairwise comparisons; resilience to uncertainty and risk, due to the ability to form a rating scale in cases where standard measurements are insufficient or incomplete and scattered data are present; transparency of the process of calculating ranks and obtaining results. The disadvantages of this method include: the need to perform numerous pairwise comparisons in cases with a large number of criteria or alternatives; the problem of disrupting the priority of objects when adding very similar alternatives or copies of their existing variants to the set of alternatives. Due to the additive method of aggregating scores, high scores on some criteria can offset low scores on others, which can lead to excessive smoothing of results and the loss of important details.

In cases where historical information on object rankings is available or expert evaluations exist, it is advisable to use LTR approaches. These methods are widely used in information retrieval, recommendation systems, and application sorting, and can be adapted to the task of planning the priority restoration of damaged urban infrastructure objects [37]. The RankNet, LambdaRank, and LambdaMART algorithms are important representatives of this field, actively used to build models that sort or rank documents or alternatives according to their relevance or significance [38]. These methods have evolved from simple pairwise document comparisons to more complex approaches that optimize list metrics such as NDCG. An important aspect of the development of these algorithms is their ability to optimize ranking via gradient descent using various loss functions that account for the specifics of ranking.

The RankNet algorithm, proposed by Microsoft Research, is the first method in the LTR family and is based on a pairwise approach. The basic idea is that the model compares pairs of documents and determines which one is more relevant. For each pair of documents (d_i, d_j), where d_i is supposed to rank higher than d_j, RankNet uses a sigmoid function to predict the probability that d_i will be better than d_j

$$P_{ij} = \frac{1}{1+e^{-\sigma(s_i - s_j)}}, \tag{15}$$

where s_i and s_j are the scores generated by the model for documents d_i and d_j, respectively; σ is a model parameter.

The loss function is based on cross-entropy, which is minimized to train the model to make accurate predictions. However, this approach focuses on minimizing the error for each document pair rather than directly on the ranking metric, which is the main limitation of this method.

LambdaRank is an improvement over RankNet – it introduces lambda gradients that allow for the optimization not just of pairwise accuracy, but specifically of list-based quality metrics such as NDCG. The idea behind LambdaRank is that, instead of adjusting the model solely based on errors in pairwise comparisons, the gradients are adjusted to minimize changes in the list quality metric caused by reordering document pairs. This allows for direct optimization of the ranking, reducing the likelihood that relevant documents will end up at the bottom of the list. LambdaMART is a further development of LambdaRank and combines the ideas of λ-gradients with gradient boosting on MART trees. This algorithm uses an ensemble of decision trees, where each tree corrects the errors of the previous one. Each tree is trained on the residual errors made by the previous trees, thereby optimizing the ranking metric while accounting for the values of the λ-gradients. As a result, LambdaMART optimizes list metrics such as NDCG and provides more accurate results with large amounts of data (both categorical and numerical). However, this algorithm is computationally complex, requiring extensive parameter tuning and retraining.

The RankNet, LambdaRank, and LambdaMART algorithms successively improve the approach to Learning to Rank: from simple models that work with document pairs to more complex methods that can optimize ranking quality using boosting techniques. Compared to previous methods, LambdaMART is the most powerful, as it combines the strength of λ-gradients and gradient boosting on trees, which allows for a significant improvement in ranking accuracy with large datasets and high variability. However, all these methods require significant computational resources and careful tuning to avoid overfitting.

For prioritizing building restoration, MCDM methods (TOPSIS, AHP) are a good choice when there are multiple criteria but no labeled data, as they offer simplicity and transparency. RankNet, LambdaRank,

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and LambdaMART are suitable for large datasets with prior estimates, as they are focused on optimizing ranking metrics such as NDCG. For tasks with limited data or expert estimates, MCDM methods will be more convenient. The TOPSIS method is simple to implement and provides a clear and intuitive ranking of alternatives based on their distance from ideal and anti-ideal solutions. It also works well when there is a limited amount of data and no need for in-depth modeling of dependencies between criteria.

4.4. Structure of the Proposed Intelligent System for Automated Analysis of Damage to Urban Infrastructure Objects

The intelligent system for automated detection of damage to buildings based on images is primarily designed to assess the extent of damage and prioritize their restoration, taking into account cultural and social significance. This system must be effective, scalable, and transparent, and be based on the integration of artificial intelligence principles, image analysis methods using computer vision, and contextual information to support decision-making regarding the order of reconstruction of damaged infrastructure objects in Ukraine

The system under development aims to address the aforementioned shortcomings of existing solutions by proposing an innovative approach to assessing damage and prioritizing the restoration of buildings in Ukraine.

The system's operation involves the sequential implementation of the following key stages: identification of damaged buildings; analysis of damage and assessment of its severity; and determination of restoration priorities, taking into account the social and cultural value of each building.

Among the advantages of the system under development is, first and foremost, the ability to obtain data on building damage from multiple sources, including satellite imagery, reports from municipal authorities and emergency services, and information from volunteers. This approach allows for gathering more information about the presence of structural damage and accounting for damage to structures that may have been overlooked during the analysis of satellite imagery. Although working with satellite imagery plays an important role in identifying damaged structures – as it allows for the rapid detection of a larger number of damaged structures – it is not mandatory.

Another advantage of this system is the ability to conduct on-site surveys, which allows for a more detailed examination of existing damage. Importantly, the system will provide not only a general assessment of the extent of damage but also a list of identified damages, enabling preliminary cost estimates for restoration work and planning for partial reconstruction of buildings in the event of insufficient funds. The system uses 3D models of buildings, which allow reconstruction specialists to examine the scope of work and the extent of damage in greater detail.

When calculating restoration priorities, the system balances a building's functionality, the extent of its damage, and its cultural value, using UNESCO standards and local registries. This ensures objectivity in the rating process, unlike similar systems from FlyPix AI and T2D2, which do not account for cultural and social aspects.

Finally, the system is transparent, giving ordinary citizens the ability to track where allocated funds are directed, thereby eliminating corruption risks. In the context of the ongoing martial law in Ukraine, where resources are limited, this advantage will ensure support from the community and donors, facilitating the rapid restoration of critical infrastructure and cultural sites.

Figure 7 shows a general diagram of the proposed system's functionality. According to the diagram in Figure 7, the process of analyzing building damage and determining the priority of their restoration proceeds as follows: first, data sources are analyzed to identify all damaged buildings and compile a corresponding list of their addresses; next, detailed information on each structure from the list is collected and analyzed; and in the final stage, a list of all surveyed buildings is created, sorted by the priority of their planned restoration, and a report is generated that includes the system's results.

To obtain information about all damaged buildings, the system is designed to interact with three different, independent primary sources. Rapid monitoring and subsequent analysis of potential damage across large areas is carried out (where possible) using satellite imagery, which enables the task of identifying and classifying damaged objects by assigning them a damage class (level). After the computer vision method completes its work, the system proceeds to the next step, which involves linking the identified building to its address and generating a list of addresses marked with the building's level of damage. Given that, in such aerial surveys, buildings are typically surveyed only from above, there is a possibility of missing buildings that have an intact roof but damaged walls and facades. To account for this type of building, the system is designed to work with two additional data sources.

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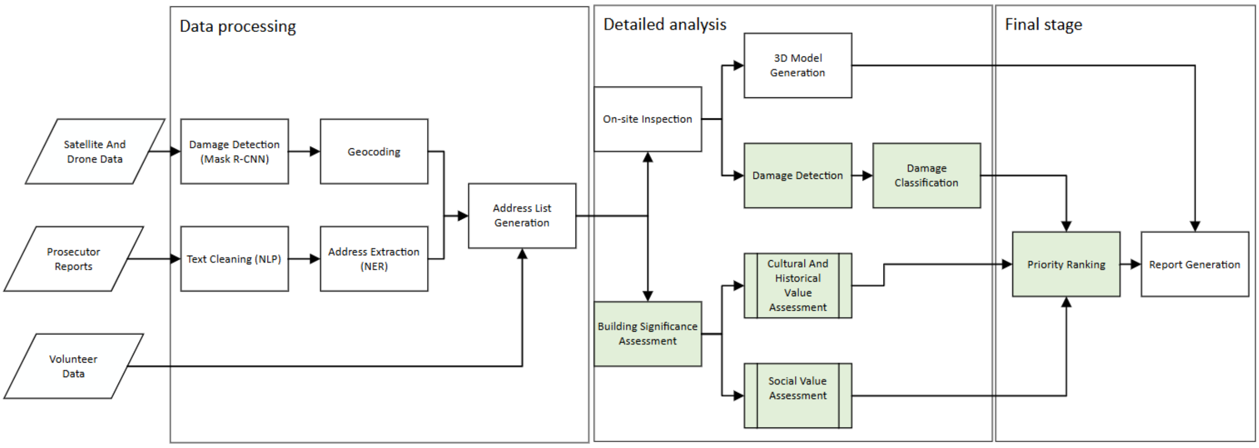

Fig. 7. General block diagram of the proposed system's functions

Typically, emergency response teams are immediately deployed to the sites of attacks to document damage to buildings. By collaborating with government agencies – such as the prosecutor's office – based on reports from these teams, it is possible to obtain addresses, photos of the damage taken from various angles, or even an approximate assessment of the extent of damage to a structure. Using these reports within the system allows for a significant refinement of the list of destroyed buildings identified through satellite imagery analysis. However, for de-occupied territories that are extensive in area and have a high level of destruction, there is often an insufficient number of such reports available. In such cases, the final information resource plays a crucial role: collaboration with volunteers and concerned citizens who can report, through established communication channels, the location of a damaged building at a specific address, subjectively assess the severity of the damage, or send photo reports. Thus, the result of the first module's work is a list of addresses generated after analyzing satellite imagery, sorted by damage severity ratings, and supplemented with information received from operational services and volunteers.

After generating this list, the system proceeds to the second stage. At this stage, all available information is searched for and collected for each building on the generated list. This stage can be divided into two independent blocks, which can therefore be executed in parallel. The first block involves working with archives and databases to obtain complete information about the building's construction history, its architectural style, the architect, significant historical events that may be associated with it, information about the building's importance to society, and its current functional role. The final step is to search for data on the type of structure. Most buildings are constructed according to standard designs, and typically, the construction information characteristic of a standard type and series of buildings applies to the structure itself. Next, following specific guidelines, the building's socio-cultural value and its social significance are determined. Both assessments are rated on a scale from 1 to 10.

The second part of this stage involves deploying mobile teams that visit all addresses and conduct on-site inspections, during which they photograph the building from all angles to obtain the most comprehensive information about its condition. It is also permissible at this stage to record a video of a full walk-through of the building, if possible. After the collected information is entered into the system, the stage of automated visual analysis begins using computer vision methods to detect various types of damage. The next step involves determining the extent of the building's damage by correlating the identified types of damage with a ten-point scale, ranging from minor to critical damage. The video footage obtained during the survey is processed separately using algorithms that implement Structure-from-Motion (SfM) reconstruction, resulting in a detailed 3D model of the structure. This allows specialists to conduct a more detailed preliminary assessment of the scope of repair work without the need for a physical site visit.

In the final stage, the ranking method implemented in the system integrates the previously obtained indicators (level of damage, cultural and historical value, and social significance) into a single priority metric.

The result of the entire system is a priority-sorted list of damaged sites and detailed reports on each of them, containing information on defect types, a 3D model, and an assessment of sociocultural value.

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4.5. Software Implementation of Project Modules

The system for prioritizing building restoration, taking into account automatically detected damage, the calculated damage severity score, its social significance, and cultural value, was created as a client-server web application, with the server-side implemented using Flask. When building this project, the principle of separation of concerns was followed; that is, the project structure is organized in such a way as to ensure its modularity, ease of maintenance, and the ability to expand functionality in the future. Figure 8 shows the structure of the project's software components in the development environment.

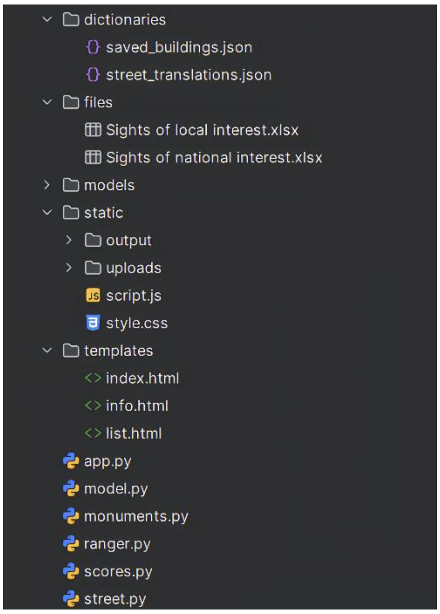

Fig. 8. Structure of the project's software components

The project consists of the following components:

– the "dictionaries" directory, which contains files with reference information required for data processing. The saved_buildings.json file stores records with data on damaged buildings for ranking purposes. This file serves as a database that is accessed when there is a need to display a list of all damaged addresses on a web page and to add a record after inspecting a new damaged building. The street_translations.json file is a user dictionary and contains the correspondence between old and new street names in the city, enabling the correct translation of street names from various languages into Ukrainian. This file is used in the application to retrieve all necessary information about a building, which comes from various sources where it is stored in different formats and has different street name conventions;

– the files directory, which contains xlsx files downloaded from the official website of the Ministry of Culture and Strategic Communications of Ukraine, as well as from the State Register of Immovable Monuments of Ukraine. This directory contains the files Sights_of_local_interest.xlsx and Sights_of_national_interest.xlsx, which contain information about sites of local and national cultural significance, respectively. These files are used as a data source for assessing the cultural and historical significance of buildings;

– the models directory, which contains the weights of pre-trained deep learning models that can be used to detect damage in images of buildings. This directory is critical for automating the image analysis process and generating a vocabulary that reflects damage classes and the number of instances of each class detected in an image;

– the static directory, which stores the web application's static resources. It contains the output and uploads subdirectories, used to store the results of image processing by the computer vision model and user-uploaded images, respectively. In addition, the script.js and style.css files implement the dynamic behavior and styling of the client-side application interface;

– the templates directory, which contains HTML templates for rendering the web interface. In particular, the files index.html, info.html, and list.html display the home page, detailed information about buildings, and a list of results, respectively;

– the venv library root directory, which represents a Python virtual environment used to isolate project dependencies;

The project's root directory contains scripts that form the core of the project. All project functionalities are implemented in various Python files, namely:

– app.py, which is the main application file that initializes the Flask server and contains defined routes for server-client interaction as well as the general logic of the web interface;

– model.py, which is the module responsible for loading and using a pre-trained deep learning model to detect damage in images;

– monuments.py, which contains the logic for working with data on historical and cultural sites and the results of processing the corresponding Excel files;

– ranger.py, which implements a mechanism for multi-criteria ranking of objects using the TOPSIS method;

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– scores.py, which is a module for calculating three key building assessments: damage level, functional significance, and cultural value;

– street.py, which contains functions for processing addresses, including street name translations, dictionary lookups, and queries to various databases and archives to obtain all necessary information about the building.

The performance of computer vision models used to detect damage in building images depends significantly on the quality of the training dataset. Therefore, the task is to prepare such a dataset with a sufficient number of images that are correctly annotated. Given that there is a limited number of high-quality images available for the tasks of implementing the proposed system, it is advisable to combine several relevant datasets. However, this raises issues regarding the quality and detail of annotations in such image sets. In the selected combined dataset for analyzing the condition of damaged buildings, a general "damage" class was defined, which is used to assess damage of all levels. To provide the model with greater flexibility in detecting different types of damage, the system performs autonomous image annotation.

Work with the dataset was conducted on the Roboflow platform using semi-automated annotation tools. Figure 9 shows the interface window for image annotation, where the annotated image is displayed on the right and information about the labels of the defined classes is shown on the left. Image annotation requires the development of a comprehensive list of damage types to most accurately identify different classes of damage, which vary in severity. After conducting a detailed analysis of various survey reports on damaged buildings, as well as a visual inspection of the available dataset, it was decided to define the following basic classes: Big-Crack, Medium-Crack, Small-Crack, Collapsed wall, collapsed building part, damaged roof, burn marks, damaged facade, broken balcony, broken door, and broken window. Note that the datasets subsequently used for training and testing the system's computer vision models contain a greater number of different damage classes.

The defined list of classes allows for the coverage of a wide range of damages, thereby eliminating the issue of subjectivity in determining which class a particular damage belongs to. To definitively avoid errors during dataset annotation, it was appropriate to define a damaged facade as a breach in the building's outer layer (e.g., cladding), a destroyed wall as a breach in the wall's integrity, and a destroyed part of the building as a breach involving two or more adjacent walls. A burned facade is a type of damaged facade defined to distinguish damage caused specifically by fire, which has no direct impact on the structure's stability but may indicate the presence of internal damage.

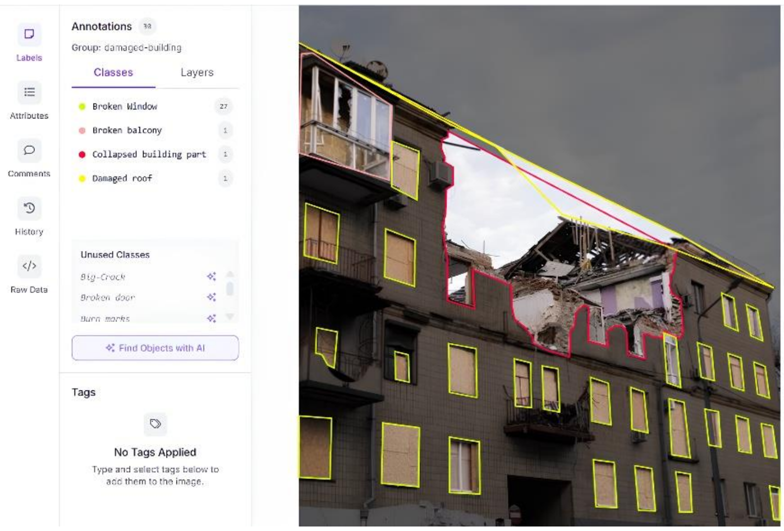

Fig. 9. The interface window of the Roboflow visualization environment

Figure 10 shows, for comparison, images with the initial annotations (left) and those resulting from the automated annotation process (right). After annotating the base test dataset, the final version contained 383 images across 11 annotation classes. A total of 12,973 annotation masks were applied. Most of the annotations were created for the broken windows class (10,234) and the damaged facades class (1,629). All other classes have a total of between 100 and 600 annotations. The class with the fewest annotations is the class of small cracks – 114 annotations.

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Fig. 10. Comparison of the original and annotated images of damaged buildings

The significant class imbalance is due to the varying nature of the damage and the different frequencies at which it occurs. This imbalance can significantly affect the accuracy of damage detection models, causing them to analyze the most prevalent classes more thoroughly than other classes. This issue was addressed later, during the model training phase. After annotating the image set is complete, the analytical information automatically generated on the Roboflow platform is analyzed. Selecting the optimal features for the dataset allows us to subsequently determine which model to prioritize and plan the preparation of the dataset for its training. To address the issue of varying image dimensions during the dataset creation phase, it is necessary to standardize the size for all images. Typically, images are resized to 640×640, but given the large number of small-sized defects, it was decided to resize the images to 1024×1024, which will slow down model training but improve the quality of defect detection. Figure 11 shows an Annotation Heat Map, which visualizes the distribution of annotations across the entire image space in the dataset.

As can be seen, the central region (red and orange zones) contains the highest concentration of annotations, while the periphery (blue zone) contains virtually no objects. This pattern indicates a spatial bias – most detected objects are located in the center of the images. This can lead to overfitting, where the model expects the objects needed for detection to be in the center of the image and may fail to detect them in other areas. To address this spatial bias issue, geometric transformations are typically used. However, since all images contain buildings with a fixed spatial location, the most effective approaches that can be used in our case during the augmentation stage remain the Crop method, which will force the model to see objects in different parts of the image, and the Shear method, which allows the data to be made more geometrically diverse without distorting orientation. Using only these augmentation processes to address the previously described dataset issues, a version of the image set comprising 696 photographs was created, which can now be used to train computer vision models. To further increase the number of images, augmentation procedures such as brightness adjustment, image blurring, and noise addition can be used. This not only increases the number of images in the dataset to 4,048 but also makes the model more robust to varying shooting conditions and the quality of the input images. Thus, at this stage, image datasets were created for training models to recognize building damage.

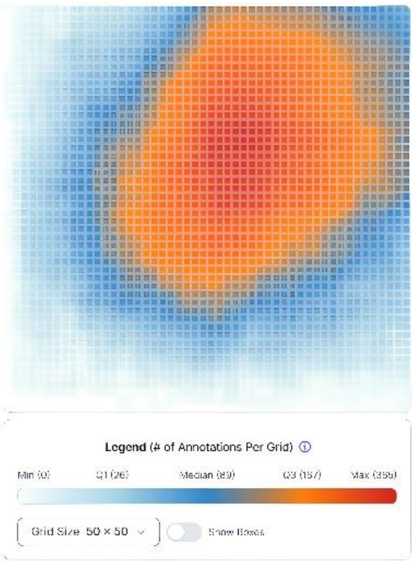

Fig. 11. Annotation density map

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Let's take a closer look at the implementation details of the main modules of the proposed system: the damage detection module, the building assessment calculation module, and the object ranking module.

The main function of the *damage detection module* is the predict_and_visualize_return_data function, which is responsible for applying the weights of a pre-trained damage detection model to the required images and preparing the output data for further analysis and visualization. At the initial stage of the function's operation, the model weights are loaded as a dictionary, where each key corresponds to a specific model from several available options. Next, the original image in BGR format is read using the OpenCV library. The image is processed by the selected model with a specified confidence threshold of 0.5 on a CPU device. The result of this processing is an object containing information about detected bounding boxes, masks, and damage classes. In the next step, the number of objects in each class and the total area of the segmented regions are calculated. For this, a counter is used, which is incremented for each detected frame, and the pixel areas of the masks are accumulated in the variable "total_area_pixels". After obtaining all necessary statistics, the "plot" method is called to generate an annotated image with overlaid masks, which is returned in RGB format by default. Since the subsequent saving is performed using OpenCV in BGR format, a function is used that reverses the color order (RGB→BGR) when the input array has three channels. After completing all previous steps, the resulting image is saved. The save function creates and returns a dictionary with three keys: the path to the saved image, statistics on counted objects by class, and the total area of the segments in pixels. Thus, the module provides a convenient way to obtain an image with analysis results and detailed information about the number and size of detected damages.

The building assessment calculation module consists of three interconnected submodules that sequentially determine the cultural and functional values and the degree of damage to the building. Each submodule is implemented as a separate function that takes the object's metadata as input and returns a numerical score ranging from 1 to 10. As a result, these ratings are stored in a single scores dictionary, which is subsequently used by the ranking module. The cultural value assessment function analyzes information about the protected site's status, date of construction, architectural style, and the building's architect. First, the system checks whether the building is listed on the UNESCO, national, or local heritage lists, with the highest score given to World Heritage sites, the middle score to sites of national significance, and the lowest to those with local or undetermined status. Next, the year of construction is analyzed, allowing for additional points to be awarded based on the structure's age: the oldest sites are given higher priority in terms of cultural significance. The architectural style is checked for inclusion in the list of rare schools, which allows for the identification of structures representing architectural movements important for preservation. After that, information about the architect is processed: mention of the participation of famous architects in the building's construction adds extra points to the score. After analyzing all available information, a final result is generated, which is adjusted depending on the type of building – cultural sites receive additional points, while ordinary residential buildings constructed according to standard designs, conversely, lower the final score. The resulting value is normalized relative to the maximum possible score and rounded to a whole number, with a range limited to between one and ten. The functional assessment is based on an analysis of the building's purpose and its current condition. First, the key "purpose/name" field of the building is analyzed to determine its type: residential, hospital, educational, commercial, or industrial. Each type corresponds to a base number of points, and the presence of a secondary commercial function (e.g., a residence with a store) provides a slight advantage over a standard residential building. Next, the current technical condition of the structure is taken into account – a building in use receives additional points, while neglected or abandoned structures, on the contrary, lower the score because they are not a priority for restoration. In the case of residential complexes and private homes, if data on the number of apartments is available, the scale of the property is taken into account: large complexes receive additional points, given that they are used by a significant number of people. Finally, a final adjustment based on the type of structure is added to the total score, after which the result is normalized to a scale of 1 to 10. The damage assessment function relies on the results of the computer vision module, which determines the number of objects in each damage class, and on construction information obtained from open sources. When calculating the assessment for each type of damage, a specific weight is assigned, reflecting the danger such damage poses to the building's stability. Next, a correction is added to the

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base contribution for each type of damage, taking into account the number of objects of that class found. For large numbers, multipliers are applied, even if the damage is not severe. If additional data on the building's structural features is available (e.g., the material of exterior or load-bearing walls, the presence of a technical floor, etc.), these parameters adjust the weight of each type of damage according to its impact on the structural integrity. After accumulating the total damage score, the entire indicator is normalized and scaled to a general scale, and the resulting value is limited to a range from 1 to 10. Thus, the assessment calculation module provides a multidimensional qualitative analysis of each building, taking into account historical-cultural, socio-functional, and technical characteristics, and generates input parameters for the multi-criteria ranking model.

The object ranking module is critical for determining the priority of building restoration. For ranking in this module, the TOPSIS algorithm is used, with the implementation of the main function topsis_rank and the auxiliary function _to_number. The auxiliary function _to_number is needed only to correctly convert the input rating value to an integer, preventing the program from crashing due to incorrect or missing data. The main ranking function topsis_rank takes as input a list of buildings, each of which is represented by a dictionary with a nested sub-dictionary scores containing the values of three criteria: degree of damage, social significance, and cultural-historical value. Additionally, two parameters are passed – vectors of criteria for the ideal and anti-ideal examples, containing the values of the criteria considered the best and worst in terms of the priority of the object's restoration. At the start of the system's use, the criterion values for the best and worst cases were defined as follows: a building that should be restored in the near future must have the highest social significance (10 out of 10 possible), while its cultural significance must be average (5 out of 10), because a low value would not reflect its cultural value, while a high value would likely impose restrictions on restoration and require special techniques for rebuilding the building, which is costly and not always feasible in practice. The most acceptable level of building damage should be 3, because a value that is too low may indicate only damage to windows and minor damage to the facade, which does not threaten the building's stability and therefore the building can still be used for some time without restrictions; A high damage rating indicates a possible need to demolish the building, and therefore does not require restoration work. A building that can be restored last is a socially insignificant structure with no cultural significance. If the damage level of such a building is 9, this indicates significant damage to the building. If such a building is not a cultural monument, it is advisable to demolish it rather than restore it. During the execution of the topsis_rank function, the following steps are performed for each object individually: retrieving the values of the three scores from the scores sub-dictionary; processing each criterion value using the _to_number helper function to ensure algorithm stability and prevent errors caused by missing or incorrectly formatted data; forming a score vector. Next, the distance between the current building's vector and the ideal vector is calculated, as well as between that vector and the anti-ideal vector. This determines how close or far the object under consideration is from the ideal or, conversely, from the worst possible option. Based on the values of these two distances, an aggregated proximity index to the ideal solution is calculated. This index takes a value between 0 and 1, where a value close to 1 means that the building is closer to the ideal scenario and, accordingly, has a higher priority in the ranking. After calculating the index for each building, the list of all building records is sorted in descending order of this index, meaning that the highest-priority buildings appear at the top of the list. Additionally, each object is assigned a priority_rank field, which determines its order number in the sorted list, starting with 1 for the object with the highest index. Thus, as a result of executing the specified function, two additional values are added for each building in the input list: topsis_score, which contains a numerical indicator of proximity to the optimal solution, and priority_rank, which indicates the building's position in the overall priority ranking. The function returns an updated list of buildings, sorted by importance, which is then displayed to the user. This approach, using the topsis_rank function, allows for more informed decisions regarding the order of building restoration, taking into account not only their technical condition but also their social and cultural significance.

4.6. Server-side component of the system

The server-side component of the application is implemented as a Flask application and serves as the single entry point for all client requests. It handles HTTP request routing, coordinates calls to all necessary functions for retrieving and preparing data from external services, calculating scores, and saving them.

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The main route at the path "/" is required to process the GET request and read the saved_buildings.json file, which contains saved records of buildings with preliminary analysis results. If such a file exists, its contents are deserialized into a list of objects; otherwise, an empty array is created. In the next step, this list is passed to the list.html template, which is responsible for displaying a tabular list of buildings with their addresses and previously calculated ratings. A GET request to the /add route returns an empty form implemented in the index.html template, where the user can upload a photo and enter the building's address.

After submitting the form, a POST request is sent to the /upload route. The image file and a string containing the building's full address are sent to the server, after which the function handling this route checks for the image's existence and saves it to the static/uploads folder. Next, the predict_and_visualize_return_data function is called, which is responsible for running the pre-trained damage detection model on the user-uploaded image, and then returns the path to the saved annotated image, the count of detected damage classes, and the total area of the masks.

In the next step, the house number and street name are extracted from the received string containing the building address, after which a request to an external source (web scraping) is initiated via the get_building_info function, which returns a dictionary of keys containing basic and additional information about the building obtained from open sources. Fields for both types of information are filtered according to a predefined list, retaining only relevant attributes. If the external search yields information about the building's series and design, the get_project_info function is called, which searches for the necessary information about standard building series and designs and returns a dictionary with the retrieved data, which is also stored in the session. The find_monument_info function is used to search for data regarding the status of the historical and cultural monument. After all necessary data has been prepared, the user is redirected to the /info route, where the info.html template displays: an annotated photo, a damage counter, and basic and additional information about the building.

The /scores route is implemented as an API method that returns the results of three evaluation functions – estimate_damage_severity, estimate_functional_value, and estimate_cultural_value. It passes the necessary data previously stored in the session to the corresponding submodules, returning a JSON object with three numeric fields: damage, functional, and cultural. This route implements asynchronous updates of building assessment values on the client side without reloading the web page. To save the retrieved building information and calculated assessments, the user makes a POST request to the /save route. After that, the server reads the address and damage statistics from the session, and the final values of the three ratings from the request body, then sends a new record to the saved_buildings.json file and confirms successful saving. The GET route /list, which replicates the functionality of the main page, is designed to display only records that have already been saved. The /topsis route triggers a re-ranking of all records when a new building record is received from the user. After the re-ranking is complete, the session rewrites the saved_buildings.json file according to the new restoration order and redirects the user back to /list, where the updated ranking is displayed.

Thus, the server-side component of the Flask-based application provides a complete data lifecycle: from image loading and analysis (through external data processing and score calculation) to their storage and multi-criteria ranking. This architecture allows for scaling functionality and integrating new services or modules without significant code refactoring.

4.7. System User Interface

Upon launching the application, the user immediately receives a list of buildings that were damaged during military operations and require restoration, presented as a pre-sorted list (from buildings requiring the most urgent intervention to those that can wait for new investments). Figure 12 shows the appearance of the application's main page.

After reviewing the list of damaged buildings, the user can add a new entry – register a new damaged building – by clicking the "Add Entry" button. After clicking this button, the user is redirected to a page for adding a record to enter the building's address and upload one or more photos of the building from different angles. After the user clicks the "Submit" button, the uploaded information is processed and sent to the server. A search is conducted at the specified address for general information about the building, information about the standard design according to which it was built, and a check for the address's presence in the registers of local and national heritage sites. At the same time, the uploaded images are processed for automatic damage detection. The status of these processes is displayed on a separate page to allow users to track the progress.

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List of saved buildings

Priority	Address	Number of damages	Destruction	Func. value	Hist.-cult. value
1	Constitutsii Square, 1	Broken Window: 71 Damaged roof: 1	4	7	6
2	Rymarska Street, 20	Broken Window: 33	2	7	5
3	Rymarska Street, 19	Broken Window: 17	1	7	6
5	Lesia Serdiuka Street, 54	Broken Window: 72 Broken balcony: 2	3	7	1
6	Heroiv Kharkova Avenue, 94	Broken Window: 7 Damaged facade: 1	2	5	5
7	Sumska Street, 25	Broken Window: 14	1	5	3
8	Yaroslava Mudroho Street, 15	Broken Door: 1 Broken Window: 12 Damaged facade: 1	2	5	1
10	Yaroslava Mudroho Street, 13	Broken Window: 18 Damaged facade: 1	3	5	1
11	Sumska Street, 61	Broken Window: 11	1	1	7

Add entry Rank

Fig. 12. The app's home page

Figures 13 and 14 show what this page looks like after the user has uploaded all the necessary data and sent it to the server. After reviewing the building information, the user can calculate the ratings needed for ranking by clicking the "Get Ratings" button. A pop-up window (Fig. 15) displays the automatically calculated ratings and comments, which the user can save.

The pop-up window (Fig. 14) displays automatically calculated estimates and comments, which the user can save.

Building information

Balcony/loggia	balconies
Ceiling height	2.48 m
Internal walls	concrete multi-hollow panels (0.22 m), gypsum-concrete partitions (0.08 m)
Additionally	—
External walls	brick, silicate brick (thickness 0.35–0.45 m)
Facade exterior	sometimes ceramic tiles
Apartments in bldg.	1-, 2-, 3-room apartments
Number of entrances	2-8
Floor slabs material	oval-hollow or hipped reinforced concrete panels
Disadvantages	small kitchens, moral and physical aging of the building series, cracking of the external brick load-bearing walls due to poorly burnt brick

Fig. 13. The first section of the page containing information about the building

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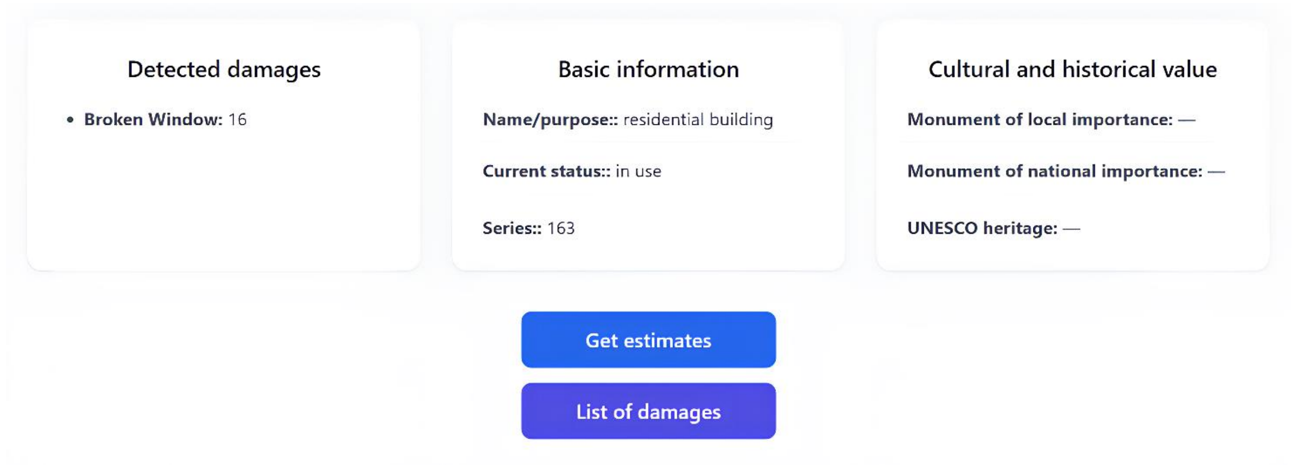


Fig. 14. The second part of the page containing information about the building

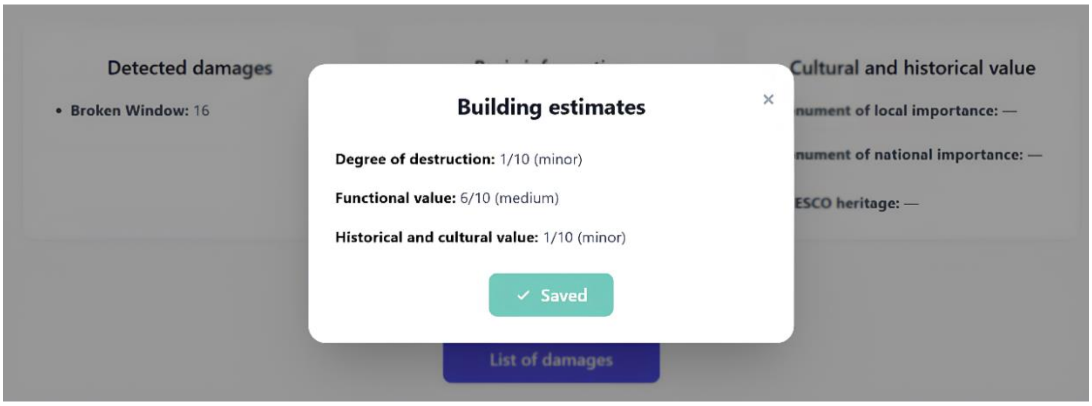
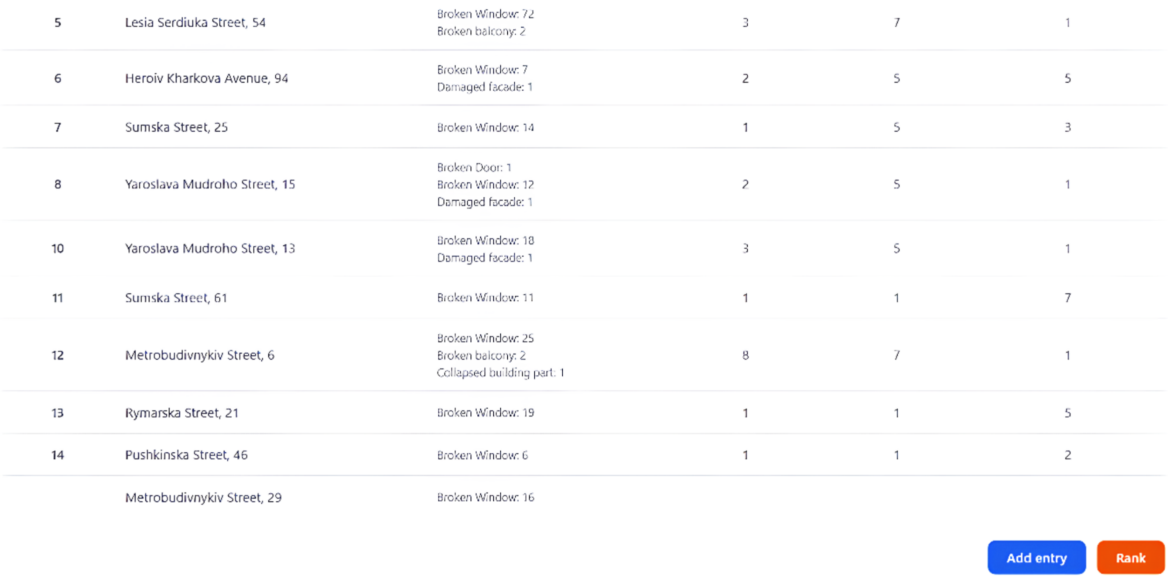


Fig. 15. Pop-up window displaying the estimates calculated for the building after the information has been saved

After saving the building record – including its address and ratings – the user can navigate to the page listing all buildings to verify that the building has been added to the list of buildings registered for restoration, but that a restoration priority has not yet been assigned to it. An example of the page listing buildings in this state is shown in Fig. 16.



5	Lesia Serdiuka Street, 54	Broken Window: 72 Broken balcony: 2	3	7	1
6	Heroiv Kharkova Avenue, 94	Broken Window: 7 Damaged facade: 1	2	5	5
7	Sumska Street, 25	Broken Window: 14	1	5	3
8	Yaroslava Mudroho Street, 15	Broken Door: 1 Broken Window: 12 Damaged facade: 1	2	5	1
10	Yaroslava Mudroho Street, 13	Broken Window: 18 Damaged facade: 1	3	5	1
11	Sumska Street, 61	Broken Window: 11	1	1	7
12	Metrobudivnykiv Street, 6	Broken Window: 25 Broken balcony: 2 Collapsed building part: 1	8	7	1
13	Rymarska Street, 21	Broken Window: 19	1	1	5
14	Pushkinska Street, 46	Broken Window: 6	1	1	2
	Metrobudivnykiv Street, 29	Broken Window: 16			

Fig. 16. Example of a page displaying a list of buildings after creating a record for the added building

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To include the added building in the restoration priority list, the user must click the "Rank" button, after which the list of buildings will be updated to reflect the newly added entry.

5. Research Results

To evaluate the effectiveness of object detection and segmentation models under conditions of severe class imbalance in the dataset, two architectures – YOLOv11 and Mask R-CNN (implemented via the Detectron2 framework) – were trained and investigated. Model training was conducted using several strategies aimed at improving the recognition quality of objects from rare classes, namely: the baseline approach, data augmentation, the use of a weighted dataloader, and a combination of augmentation with a weighted dataloader. We will now examine the specifics of training and tuning the selected instance segmentation models, as well as perform a comparative analysis of the detection quality for different types of damage using the applied architectures, taking into account the class imbalance.

Images were loaded via the Roboflow API in the format required by the models, and model training was conducted in the Colab Notebook cloud environment.

The first model considered in the experiment was one of the latest models in the YOLO family – YOLOv11 with segmentation weights. This model was trained using a standard configuration adapted to the tasks at hand, employing loss functions characteristic of this architecture (including box loss, classification loss, objectness loss, and dfl loss), which are already built into the model for faster and more accurate training on image datasets with complex scenes.

To implement the second model selected for the study, Mask R-CNN, the Detectron2 library was used, which provides a convenient interface for training and evaluating various computer vision models. This model was also loaded and configured with default parameters.

Various approaches were considered to address class imbalance. The first approach was data augmentation, which included both transformations aimed at increasing data diversity (adding noise, altering brightness and contrast, random scaling) and random cropping of images. This allowed us to diversify the input images, increasing their number in the dataset and forcing the models to adapt to varying image quality and different shooting formats. The second approach allowed the model to account for small objects and minority objects, which occupied too little area in the original large images for effective recognition. This approach did not require additional tuning of the model training processes but was implemented by loading a different version of the dataset with the changes incorporated into it.

The third approach to solving this problem involves using a weighted dataloader, which selects training examples based on class weights and increases the probability of images containing rare objects being included in a batch. This approach was implemented on the first version of the dataset, which was not augmented, requiring the addition of the YOLOWeightedDataset and CustomTrainer datasets to the main training process for the YOLOv11 and Mask R-CNN models, respectively [39].

The final approach used a combination of data augmentation and the weighted dataloader. To implement it, the models were trained on an augmented dataset using the aforementioned classes to load images with weights. The resulting mAP@0.5, and mAP@0.5:0.95 scores for each combination of model and class imbalance mitigation method are shown in Table 1.

Table 1. *Evaluations of the effectiveness of damage detection in models using different approaches to reducing class imbalance*

	Model	An approach to addressing the issue of class imbalance			
		No configuration	Data augmentation	Weighted dataloader	Combination of approaches
mAP@0.5	YOLOv11	0.65	0.74	0.89	0.89
mAP@0.5:0.95		0.31	0.37	0.43	0.43
mAP@0.5	Mask-R-CNN	0.61	0.73	0.90	0.91
mAP@0.5:0.95		0.29	0.35	0.44	0.45

An analysis of the results for the metrics mAP@0.5 and mAP@0.5:0.95 shows that the use of methods to address class imbalance significantly improves the quality of predictions for both models. Data augmentation provides a noticeable improvement compared to baseline training, which is explained by the improvement in the models' generalization ability and the increased diversity of training examples. The use of a weighted dataloader demonstrates further improvement in metrics, driven by more balanced training, where models pay more attention to rare classes.

For Mask R-CNN, the combination of augmentation and a weighted dataloader yielded the best results, both for this model and among all experiments conducted. In the case of YOLOv11, combining these methods did not lead to a significant improvement in the mAP metric compared to using only the weighted dataloader.

Overall, the results presented in Table 1 confirm that the proposed solutions to the class imbalance problem are effective tools and help significantly improve the damage detection accuracy of both models.

To illustrate the damage detection results of the models, collages with four images are provided below, where the top section shows the results for the YOLOv11 model, and the bottom section shows the results for the Mask-R-CNN model. The images on the left represent the worst results obtained (for the approach without class imbalance mitigation methods), while those on the right show the best model performance (for the combination of data augmentation approaches and the use of a weighted dataloader). Images that were problematic to process were selected for the experiment (Fig. 17).

According to Fig. 17, the YOLO v11 model was able to detect a crack even without the necessary configuration, while the Mask-R-CNN model did not detect it. After completing training using a combination of approaches to address the class imbalance issue, the accuracy of damage detection by the models changed. Both models were able to detect all damage, but Mask-R-CNN showed better results (it detected the boundaries of the damage more clearly and with greater probability).

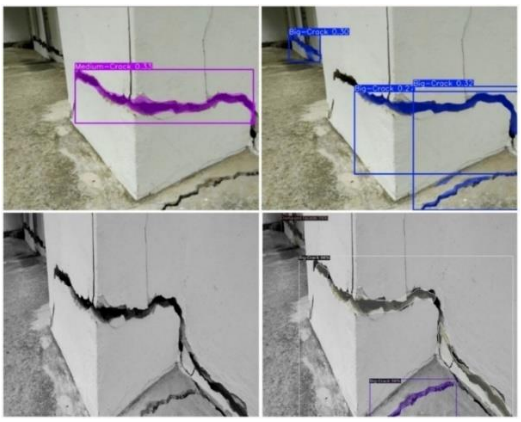

Fig. 17. Results of crack detection by the YOLOv11 (top row) and Mask-R-CNN (bottom row) models before and after applying a combined approach to address class imbalance

Figure 18 shows the results of the models on an image of a distant building containing a large number of major-class instances and a single minor-class instance. After training with default settings, the YOLOv11 model detected only the damaged windows in the building, i.e., it detected major-class instances. The Mask-R-CNN model correctly detected the boundaries for the minor class but misclassified the damage type and failed to detect instances of the minor class that had fewer pixels in the image. After training the models to account for class imbalance, both models significantly improved their performance. The YOLOv11 model was able to detect the minor class and correctly define its boundaries, while the Mask-R-CNN model correctly identified the minor class and began detecting the most obvious window damage.

Although the YOLO model was able to recognize smaller damage instances and detect a total of more instances in this case, it is difficult to declare it the clear winner. It is worth noting that failing to detect a damaged window is less serious than identifying, with lower confidence, a more severe class of damage that is actually minor. The Mask-R-CNN model identified the damage with greater confidence in both cases.

Fig. 18. Damage detection results using the YOLOv11 and Mask-R-CNN models on complex scenes before and after applying a combined approach to address class imbalance

6. Discussion of the results

After conducting a visual comparison of the models' results and analyzing the metrics obtained, we can conclude that the use of methods to address class imbalance has a positive impact, particularly on images of buildings with damage that is difficult for models to detect. Overall, both the YOLOv11 and Mask R-CNN models demonstrated high performance metrics, confirming their suitability for practical application in damage detection tasks provided that class imbalance mitigation methods are employed. Given the differences in architecture and the specifics of image processing, it is advisable to allow the user to select a model depending on the type of damage and analysis conditions. This approach will enable the system to be adapted to specific scenarios and improve the accuracy of results under real-world operating conditions.

7. Conclusions

As part of this work, a concept was developed and a prototype system was implemented for the automated detection of damage to buildings in urban infrastructure based on computer vision methods to determine the priority of building restoration, taking into account social significance, the degree of damage, and cultural and historical value. The system's performance was tested on real images of damaged buildings in the city of Kharkiv, resulting in a prioritized list of buildings registered in the system for restoration. These results can be utilized within the university's current projects, as well as in collaboration with government agencies and research institutions working on the restoration of damaged areas.

The proposed system is a development and adaptation of modern international solutions in the field of automatic analysis of infrastructure damage and multi-criteria decision-making, taking into account the specifics of the military conflict in Ukraine. Unlike existing analogues, the proposed system allows for the integration of processes for collecting available information on damaged buildings, automatically detecting damage, and prioritizing their restoration. The uniqueness of this system lies in the proposed approach to determining the priority of a building's restoration, taking into account criteria such as its social significance, historical and cultural value, and degree of damage. Experimental studies of the YOLOv11 and Mask R-CNN computer vision models and analysis of the obtained metrics allow us to conclude that the use of methods to address class imbalance has a positive effect, especially for images of buildings with damage that is difficult to detect. Overall, both models demonstrated high quality metrics, confirming their suitability for practical application in damage detection tasks. The results show that the proposed system works effectively when class imbalance mitigation approaches are applied. Given the differences in architecture and the specifics of image processing, it is advisable to allow the user to select a model depending on the type of damage and analysis conditions.

Future research is planned to further improve the functionality and performance of the proposed system. In the long term, the system could become an effective tool for supporting decision-making at the national and regional levels regarding the restoration of damaged structures, helping to accelerate the restoration of critical infrastructure and minimize the socioeconomic losses associated with significant destruction resulting from hostilities.

Conflict of interest

The authors declare that they have no conflicts of interest, including financial, personal, authorial, or any other nature, that could influence the research or the results published in this article.

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Data availability

The manuscript has no associated data.

Use of artificial intelligence

The Grammarly service (v1.2.254.1880) was used for spell-checking.

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АВТОМАТИЗОВАНА СИСТЕМА АНАЛІЗУ ПОШКОДЖЕНЬ ОБ’ЄКТІВ МІСЬКОЇ ІНФРАСТРУКТУРИ З ВИКОРИСТАННЯМ МОДЕЛЕЙ КОМП’ЮТЕРНОГО ЗОРУ

Нині актуальним є питання забезпечення інтеграції багаторівневих даних для ефективного моніторингу й аналізу пошкоджень будівель унаслідок воєнних дій на території України, а також визначення пріоритетів відновлювальних робіт. **Метою дослідження** є розроблення інтелектуальної системи автоматизованого аналізу пошкоджень об’єктів міської інфраструктури, яка б дала змогу ефективно обробляти великі обсяги зображень, отриманих з використанням засобів комп’ютерного зору, для подальшого оцінювання рівня руйнувань і прийняття рішень щодо пріоритетності їх відновлення. Надані системою детальні звіти щодо стану кожної будівлі суттєво спрощують процес експертного оцінювання без необхідності фізичної присутності фахівців на місці. Ранжування пошкоджених об’єктів за рівнем їх впливу на життєдіяльність країни забезпечує більш раціональний і зважений розподіл ресурсів, необхідних для відновлення інфраструктури. Крім того, в системі здійснюється активна взаємодія з профільними державними структурами, органами місцевого самоврядування та фахівцями, відповідальними за планування й організацію відновлювальних робіт. У межах такої взаємодії передбачається отримання доступу до комплексних баз даних з інформацією про архітектурні особливості будівель, їх історико-культурну цінність, а також використання наявної технічної документації, що дає змогу брати до уваги всі аспекти під час оцінювання серйозності пошкоджень і формування планів відновлення будівель. Аналіз інформації, отриманої під час спеціалізованих інженерних обстежень і досліджень із застосуванням високоточних інструментальних методів, допомагає додатково уточнювати параметри ушкоджень і створювати розширені датасети для подальшого навчання й валідації моделей комп’ютерного зору. Досліджено та обґрунтовано доцільність використання сегментації екземплярів за допомогою моделей YOLOv11 і Mask R-CNN, що сприяє не лише виявленню пошкоджень, а й точному визначенню їх обсягів, що є важливим для всебічного оцінювання масштабу руйнувань і планування заходів відновлення. **Результати дослідження** демонструють, що запропонована система ефективно працює за умови застосування підходів до боротьби з дисбалансом класів. Важливим етапом роботи системи є автоматизоване формування оптимізованих планів відновлення, основаних на комплексному аналізі виявлених ушкоджень. Такі плани мають зважати не тільки на технічні параметри руйнувань, а й на фінансові, матеріальні та кадрові обмеження. **Висновок.** Розроблена система є ефективним інструментом для підтримки ухвалення рішень на державному й регіональному рівнях про відновлення пошкоджених споруд, сприяє прискоренню процесів відновлення критично важливої інфраструктури й мінімізації соціально-економічних втрат, пов’язаних із воєнними руйнуваннями.

Ключові слова: аналіз пошкоджень; міська інфраструктура; глибоке навчання; моделі комп’ютерного зору; сегментація екземплярів; набір зображень; інтелектуальна система.

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