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Detection of Structural Damage After an Earthquake Using GIS and Remote Sensing Methods

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Developments in Geographic Information Systems and Remote Sensing (RS) technologies and innovative approaches emerging in deep learning (DL) supported analysis methods have an important place in disaster research as in every field. Convolutional neural networks such as Mask RCNN, U-NET, one of the deep learning methods for disaster damage impact assessment and classification, have started to show successful results. However, high-resolution geospatial imagery and drones provide faster and more accurate detection of structural damage. In this study, damaged building detection was performed using Göktürk-1 satellite images from 6 February 2023 using Mask-RCNN architecture. In this study, deep learning methods were used to detect the collapsed buildings in the city of Malatya during the 6 February 2023 earthquakes. The study aims to emphasize the significance of GIS and remote sensing for the timely and efficient evaluation of building damage after a disaster. Considering this, high quality images of Malatya city before and after the earthquake were analyzed and data sets were created by masking using Mask RCNN deep learning method through ArcGIS Pro 3.4.0 software. According to the results of the research, it quickly detected damaged buildings with an accuracy rate of 70% according to satellite images after the earthquake. As a result, GIS and deep learning models were used to detect and map the initial damage after the earthquake.

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Introduction

Cities are settlements formed in a socio-economic context where thousands of people live together. Besides, the overuse of resource consumption caused by the increasing rate of urbanization, insufficient infrastructure, disorganized planning, and poor services contribute to pose risks in urban areas (Büyüközkan et al., 2022). This situation negatively affects the resilience of cities after disasters such as earthquakes and brings along social, economic, and environmental problems.

Rapid assessment of infrastructure damage after a major disaster plays a crucial part in disaster response coordination and recovery efforts (Moradi & Shah-Hosseini). In this context, the construction of earthquake-resistant structures is of great importance. However, in cities where rapid urbanization and uncontrolled construction are common, disasters such as earthquakes can result in massive destruction, leading to significant loss of life and property. Therefore, pre- and post-disaster damage assessments have become a major focus of interest among researchers and practitioners working in the field of disaster management (Yamazaki & Matsuoka, 2007).

The first hours after the earthquake are very important. It is one of the first tasks to detect the first effects of the earthquake in these hours and to establish emergency response systems. (Dell'Acqua & Gamba, 2012; Eguchi et al., 2009; Nex et al., 2019). GIS and remote sensing technologies and the increase in satellite image quality have made it possible to use rapid assessment after disasters. (Yamazaki & Matsuoka, 2007). Considering this, the analysis of post-earthquake images derived from satellite datasets in highly urbanized areas is an effective method for visualizing the extent of initial damage. Change detection approaches involve post-classification comparison methods and image enhancement techniques, which are used to identify differences in building conditions across different time periods (Dong & Shan, 2013).

The first stage of post-earthquake emergency planning begins with assessing the current situation. Remote sensing data collected before and after a disaster offer a rapid evaluation of the built environment, making them highly valuable. Specifically, the comparison of old images and post-earthquake satellite images accelerates damage assessment in terms of time and cost. The advanced spatial analysis capabilities of GIS facilitate rapid and spatially informed decision-making for authorities. In this context, analyses based on satellite imagery play a vital role in emergency response since numerical data and satellite image analyses of pre-disaster settlements reveal post-disaster changes and provide estimations about affected populations.

After disasters, especially those affecting large areas such as earthquakes, floods, and wildfires, GIS and RS-based analyses have become widely used. High-resolution satellite imagery and aerial photographs taken by UAVs help detect the impacts of disasters within a few hours. In this context, high-resolution SAR satellite images, GÖKTÜRK satellites, etc., can quickly identify areas affected by disasters. Following analyses based on these images, the affected areas can be mapped, providing initial findings that serve as a basis for assessing the impacts of the disaster (Brunner et al., 2010).

Matsuoka and Yamazaki (2005) identified and mapped collapsed buildings using satellite imagery following the 2003 earthquake in Iran. Similarly, Balz and Liao (2010) employed SAR satellite imagery after the Sichuan earthquake to map the areas affected by the disaster. More recently, following the February 6, 2023, Kahramanmaraş (Turkey) earthquakes, numerous researchers utilized high-resolution satellite images, aerial photographs, and orthophotos to detect and map structural damage in the affected areas. In this context, Wang et al. (2023) used Sentinel-1 data to be detecting the structural damage caused by the earthquakes in Nurdağı, Kahramanmaraş, Hatay, Türkoğlu, and İslahiye. In a similar study, Du et al. (2024), Vitale and Milillo (2024), Wu et al. (2024), and Yu et al. (2024) employed SAR satellite imagery with new methods and analyses to detect building damage caused by the earthquake.

This study aims to identify, and map collapsed buildings in the Malatya caused by the February 6, 2023, earthquakes using GIS and remote sensing analysis methods based on pre- and post-earthquake orthophotos and GÖKTÜRK satellite images. ArcGIS Pro software's deep learning tools were utilized for detecting the damaged buildings in the study. The Mask R-CNN architecture, one of the deep learning methods, was employed in the analysis.

Materials and Methods

Study Area and Data Management

On February 6, 2023, two major earthquakes with magnitudes of 7.8 Mw and 7.5 Mw struck approximately nine hours apart, centered in the Elbistan and Pazarcık districts of Kahramanmaraş. These earthquakes caused widespread building collapses and severe structural damage in the eleven provinces (Kirici & Soyluk, 2023).

The designated study area, Malatya, is a mid-sized Anatolian city located near the East Anatolian Fault Zone. Geographically, Malatya lies between the coordinates 38° 21' 19.3032'' N and 38° 20' 0.6972'' E. The total population of the province is 742,725, with the Battalgazi and Yeşilyurt districts, which form the core of the study area, having a combined population of 556,068. According to post-earthquake damage assessments conducted throughout Malatya, out of 155,658 residential units in the province, 5,610 were completely destroyed, 1,840 were marked for urgent demolition, 35,620 sustained severe damage, and 2,480 were moderately damaged (Şıkoğlu, 2024).

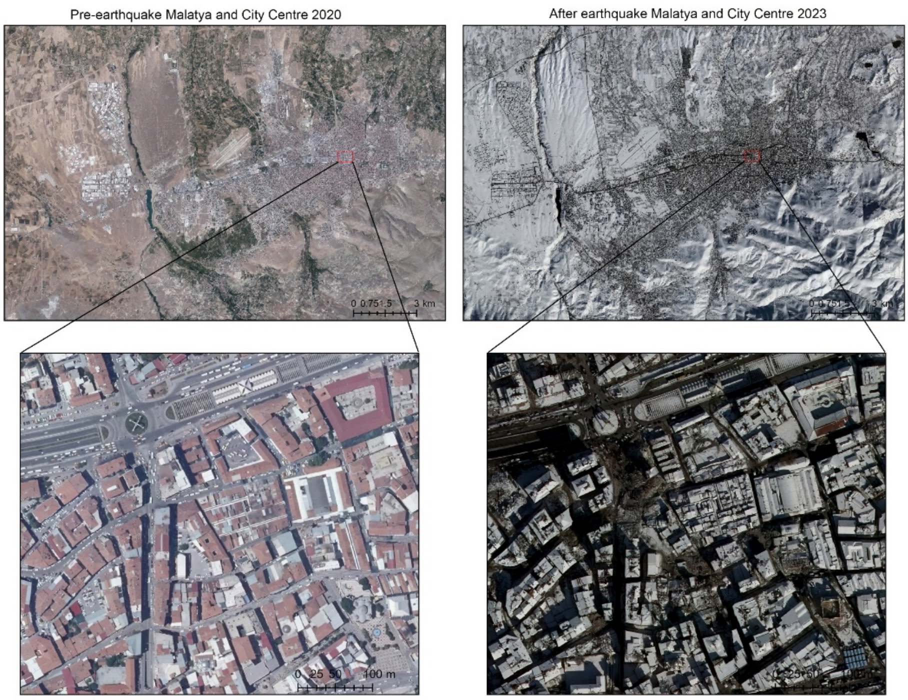

Figure 1. Study Area Before and After Earthquake

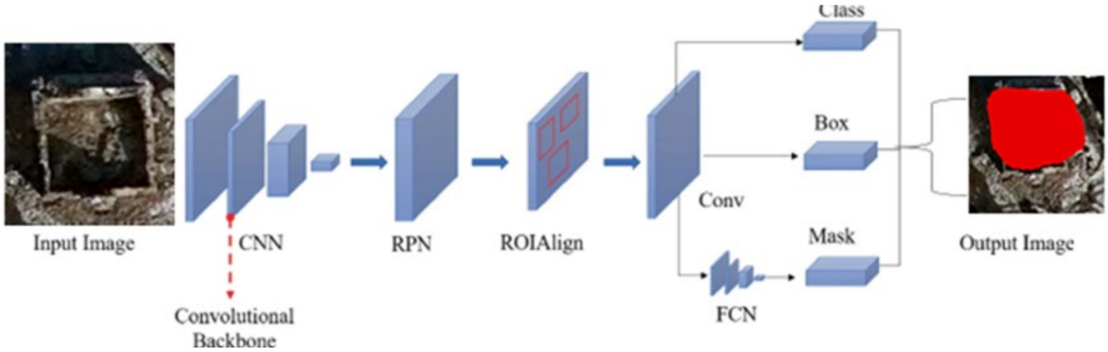

Figure 2. General architecture of the mask R-CNN (modified from Al Deen Taher & Dang, 2023)

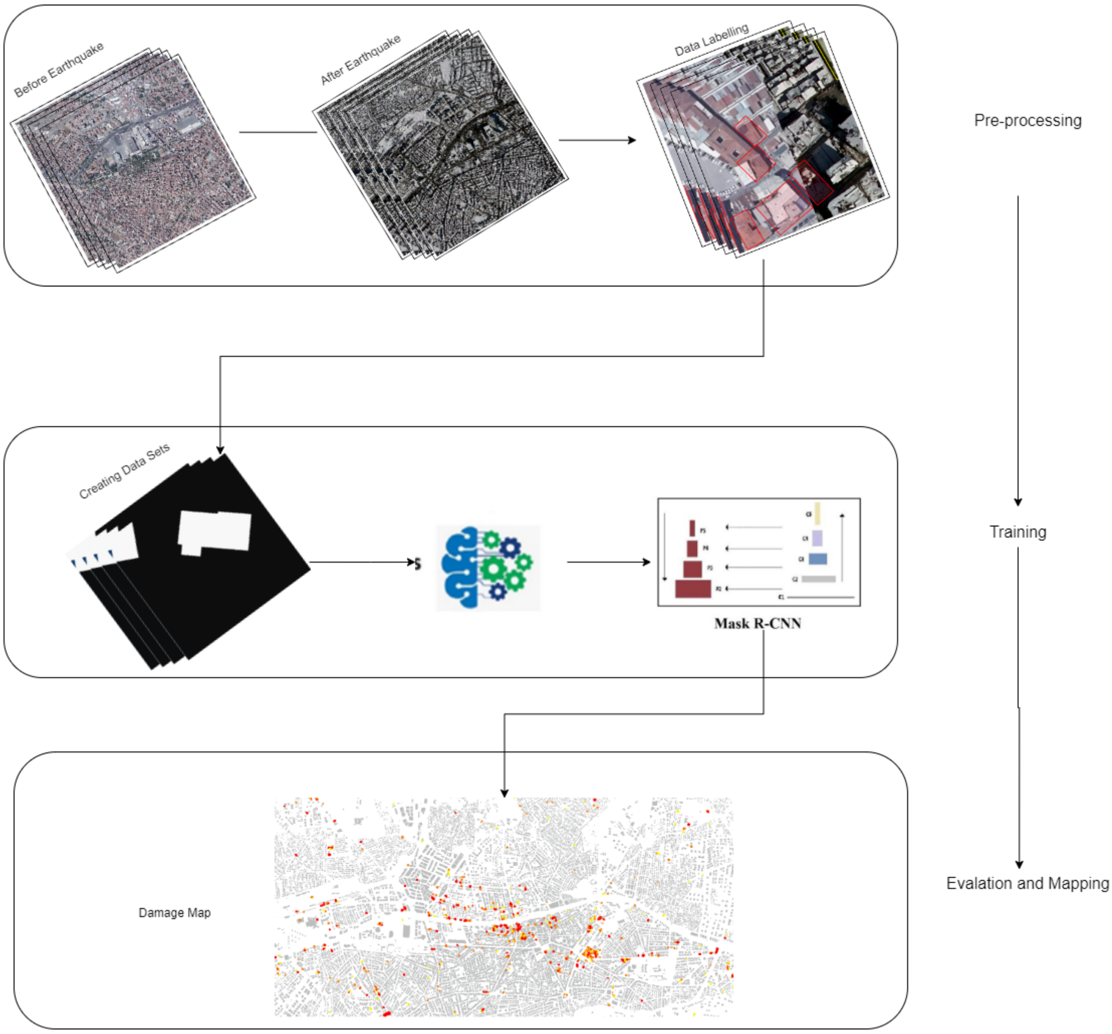

Figure 3. Proposed framework for building damage monitoring

The study, pre-earthquake 2020 orthophoto imagery provided by the General Directorate of Mapping and the post-earthquake Göktürk I-satellite imagery captured on February 9, 2023, were used. The pre-earthquake orthophoto image has a pixel size of 0.330 meters and consists of three bands. The post-earthquake satellite image has a pixel size of 0.217 meters and also consists of three bands. Both images possess high-resolution values, enabling detailed analyses for detecting structural damage following the earthquake. As shown in Figure 1, satellite images show the Malatya center, which was among the most affected areas. The test and training datasets used in the study were selected from the city center.

Methods

GIS and DL algorithms based on artificial neural networks were used to detect collapsed buildings following the February 6, 2023, earthquakes. ArcGIS Pro 3.4.0 software was utilized within the scope of the research. Deep learning algorithms are widely applied through ArcGIS Pro tools to solve spatial problems, detect objects, and perform pixel classification (Esri, 2024a).

A two-stage deep learning network was designed to address the building damage assessment problem, which involved building detection and damage grading. In the first stage, the semantic segmentation method was employed to segment buildings, drawing on methods used in previous studies. In the second stage, the damage levels of the identified buildings were classified. The ArcGIS Pro software utilized the Mask R-CNN deep learning method for the analysis. Mask R-CNN is a model capable of performing both object detection and object segmentation simultaneously, making it particularly effective for damage assessment scenarios where understanding the extent of damage is crucial (Esri, 2024b). The deep learning workflow used in the study is illustrated in Figure 2. Mask R-CNN consists of two stages. The first stage is similar to Faster R-CNN, where the Region Proposal Network (RPN) suggests a series of Regions of Interest (ROIs) along with probability scores indicating whether the regions contain objects. The key difference is that Mask R-CNN uses ROIAlign, an enhanced version of the ROIPool operation. In the second stage, the Faster R-CNN classifier is combined with an additional mask prediction head to predict both the class of the object within the ROIs and the corresponding mask (Al Deen Taher & Dang, 2023). The proposed analytical framework is based on the ArcGIS Pro 3.4.0 Mask R-CNN implementation and can be used with the licensed ArcGIS Pro software.

The Mask R-CNN algorithm was used because of its fast and high learning capability based on test data, which facilitates the processing of large data. Figure 3 shows the general workflow diagram of the method proposed in the research.

Pre-processing

Pre- and post-earthquake satellite images obtained from the February 6, 2023 earthquake were aligned using ArcGIS Pro software (Figure 4). Both satellite images were enhanced using the pan-sharpening method to improve spatial resolution. At this stage, buildings were classified based on their damage status. In the classification, buildings were labeled as ‘0’ for damaged and ‘1’ for undamaged. Additionally, roads and parks were also labeled. During the data labeling process, collapsed buildings were marked in red, undamaged buildings in yellow, roads in blue, and green areas in green. To increase accuracy, data processing was conducted in the UTM/WGS84 coordinate system. Next, the Label Objects for Deep Learning tool was used to prepare the training datasets from the post-earthquake satellite image for model training. The prepared dataset was then exported using the Export Training Data for Deep Learning tool. Finally, the data was used to train the Mask R-CNN model using the ArcGIS Pro deep learning library.

Network Architecture

Mask R-CNN is a deep learning model used for object-based boundary detection. The model was developed based on the Faster R-CNN model. Faster R-CNN consists of region-based convolutional neural networks (Region-based CNNs) that return a bounding box, a class label, and a confidence score for each object (Esri, 2024).

Table 1. Technical specifications of Göktürk-1 satellite image

Launch date	9 February 2023
Orbit	~ 681 km
Time of crossing the equator	10:30 (Local time of ascending node)
Resolution	2 m
Radiometric Resolution	11 Bit
Spectral band	0.45–0.52(Blue), 0.52–0.60 (Green), 0.63–0.69 (Red), 0.76–0.90 (Infrared)

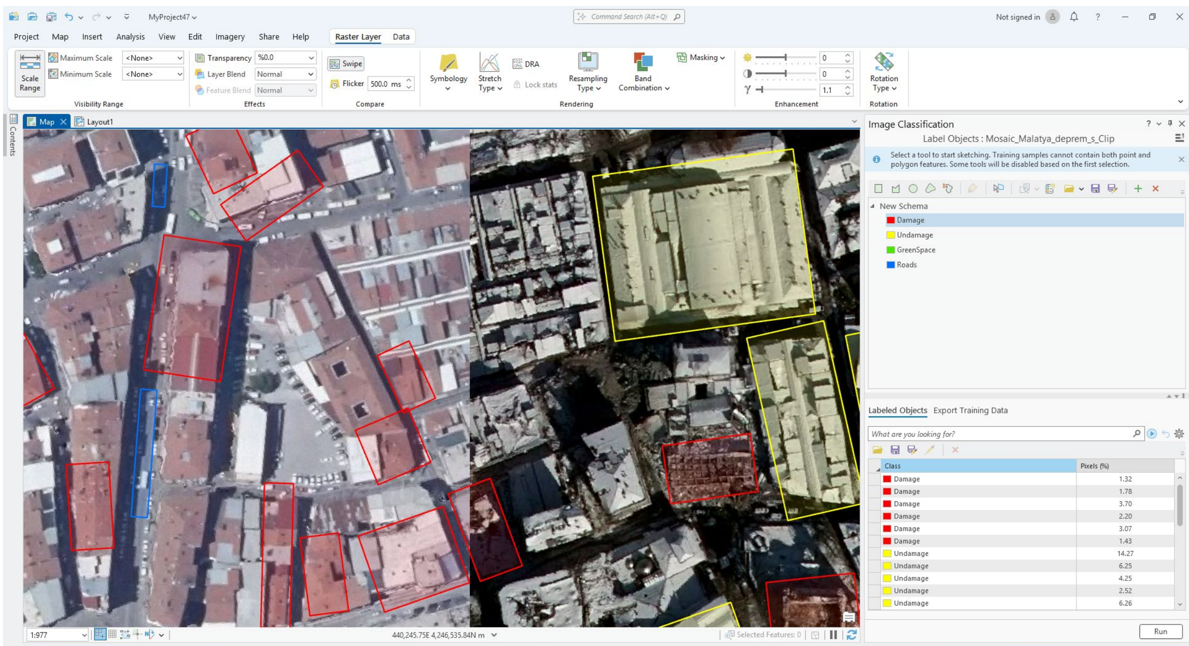

Figure 4. Creating a data set on ArcGIS Pro.

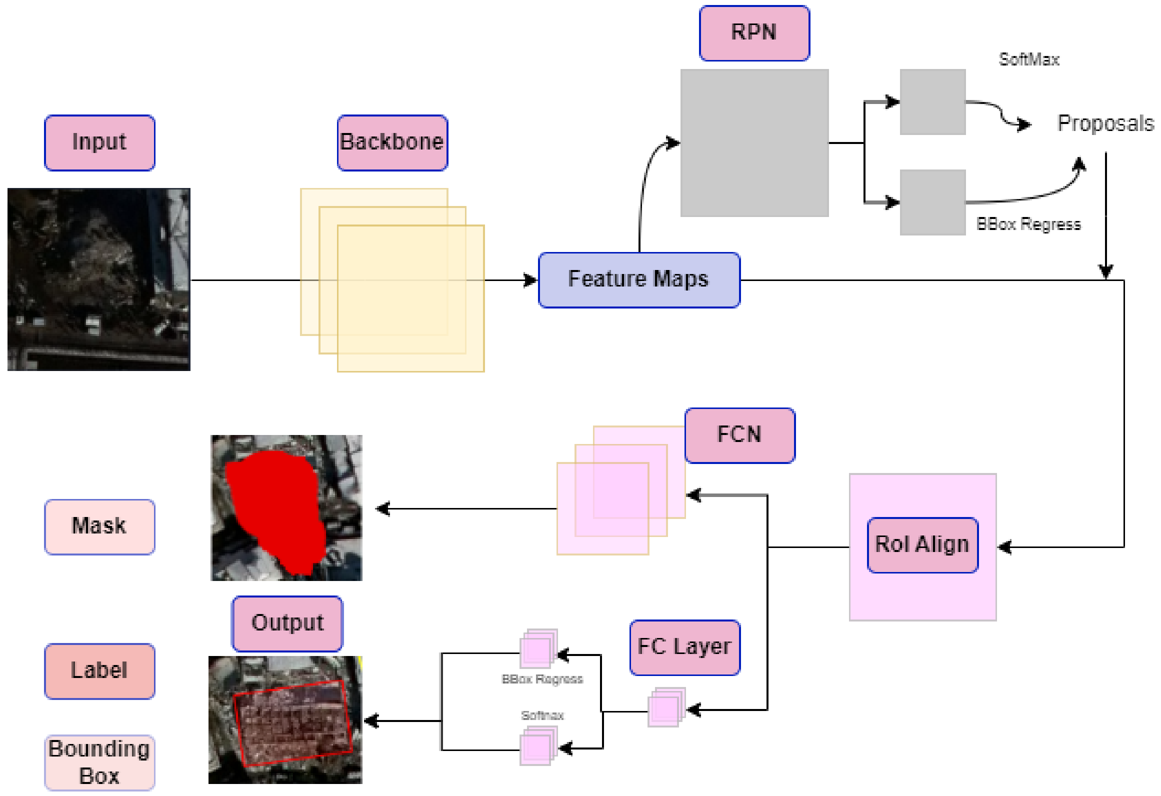

Figure 5. Mask R-CNN algorithm structure (Modified from Zhan et al., 2022)

Table 2. Summary statistics of training data

Feature	Value	CN	CV	NI	NF	MA	AA	MA
Total Number of Images	414 × 3 × 256 × 256 pixels	Damaged	0	208	257	0	440.5	3000.69
Total Number of Features	532	Undamaged	1	206	275	0.02	302.83	2762.93
Features per Image	Min: 1, Average: 1.29, Max: 4							

CN: Class Name; CV: Class Value; NI: Number of Images; NF: Number of Features; MA: Min Area (m^2); AA: Average Area (m^2); MA: Max Area (m^2)

The workflow of Mask R-CNN is as follows:

- 'Mask R-CNN processes the image through a residual network to extract features and create multi-scale feature maps.
- Side-joining is performed, and the feature maps at each stage are doubled by performing a tensor summation with adjacent lower layers.
- The feature maps are fed into the Region Proposal Network (RPN) to generate candidate regions of varying sizes. These candidate regions are transferred along with the feature maps to the Region of Interest Align (RoI Align) layer, producing bounding boxes.
- The bounding boxes are classified, and their positions are refined. A high-quality instance segmentation mask is generated for the detected object.' (Zhan et al., 2022).

Model Training

The model training was conducted on a system equipped with a 13th generation Intel(R) Core(TM) i7-13700H 2.40 GHz processor, an NVIDIA GeForce RTX 4060Ti graphics card, and 32 GB of RAM. For the study, the Train Deep Learning Model tool in ArcGIS Pro, which runs on the Keras deep learning framework, was used for the Mask R-CNN model. This tool utilizes the dataset created by the Export Training Data for Deep Learning tool and generates definitions based on the observed features. It iteratively processes the provided data to ensure the generated definitions align with the dataset (Arnold, 2023). While preparing the training data in the Export Training Data for Deep Learning tool, a coverage limitation was applied, and a damage classification layer was created. A total of 414 training samples were used, consisting of 208 samples representing collapsed buildings after the earthquake and 206 representing other structures. The Train Deep Learning Model tool was configured with ResNet50 as the backbone model.

Results

In this study, post-earthquake damage assessment was conducted using deep learning algorithms applied to satellite imagery within ArcGIS Pro 3.4.0 software. The Mask R-CNN model was leveraged, trained with the ResNet50 backbone architecture. For training the Mask R-CNN approach for building damage detection, 20 epochs were defined. Although ArcGIS Pro offers the maximum epochs value as an optional setting, it was set to 20 by default in this study to ensure balanced training of the data. Increasing this value could lead to overfitting. Additionally, raising the number of epochs prolongs the data analysis process. Considering the critical importance of the first 72 hours following a disaster such as an earthquake, keeping the number of epochs reasonable and expediting the analysis process is crucial.

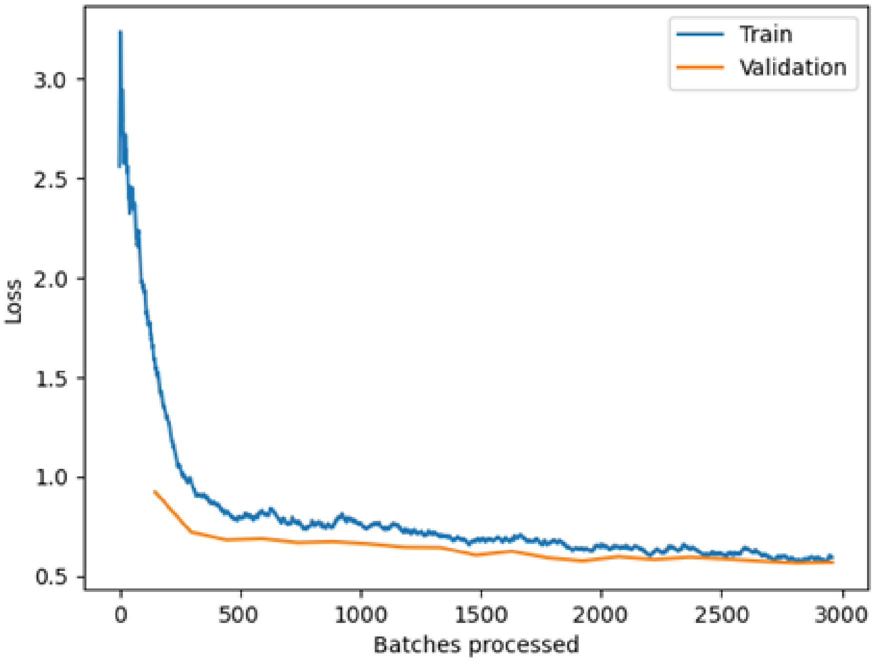

Figure 6. The relationship between the loss of training data and epochs

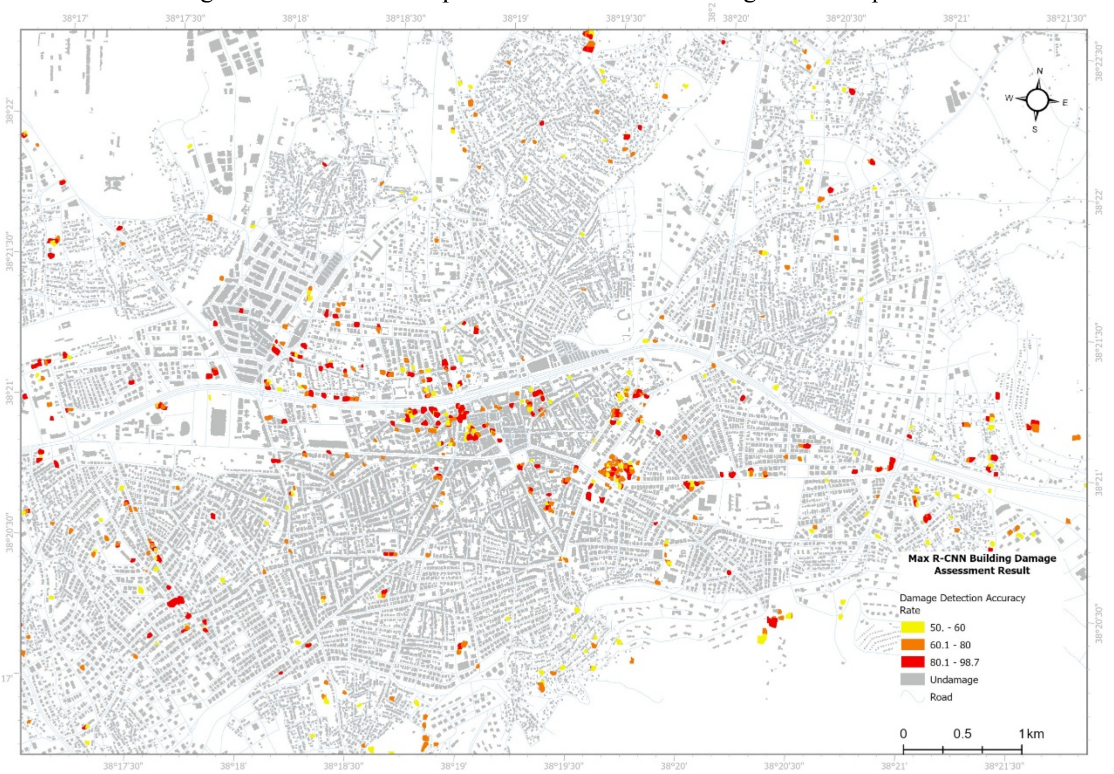

Figure 7. Deep learning result map generated using Mask R-CNN algorithm

The accuracy rate of the analyses conducted in the context of the study was calculated as 71%. This indicates that the proposed method in the article is sufficiently accurate. However, in analyses performed using methods such as deep learning after a disaster like an earthquake, a higher confidence interval is generally expected. Since this study focuses on identifying collapsed buildings after an earthquake, each vector data point during the assessment was scored with an accuracy rate ranging from 0 to 100. The closer the accuracy rate is to 100, the greater the damage in that area caused by the earthquake. When Figure 7 is examined, it is evident that the city center and its surroundings were significantly affected by the earthquake. Based on the analyses, areas with an accuracy rate of 80 or higher were determined to be completely destroyed. The undamaged data from the map basemaps represent the rasterized version of the existing building stock.

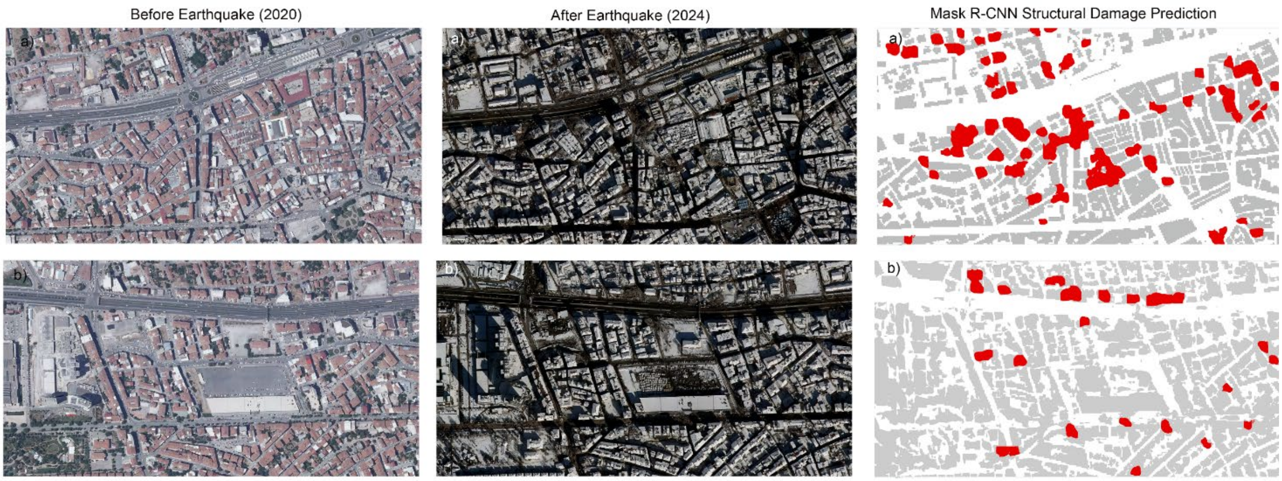

Figure 8. Visualization problems

In the satellite image-based analyses conducted using the Mask R-CNN algorithm, it was observed that some classifications were incorrectly labeled by the algorithm. The primary reason for this issue is that the analysis was performed solely based on the rooftops of the buildings. Additionally, the presence of snow cover in the satellite imagery used in the analysis further complicated the model's learning process (Figure 8).

Discussion

The analyses conducted on pre- and post-earthquake images demonstrate that the identified collapsed buildings closely match the actual damage results. However, since the images used do not contain information on the structural components of buildings (e.g., columns, beams), the detected damage is limited to the roof. Therefore, significant differences may exist between the damage identified using satellite imagery and the actual structural damage. Nevertheless, the purpose of this study is to rapidly identify collapsed buildings after an earthquake, estimate the number of structures requiring inspection, and assess the number of affected individuals to initiate an effective search and rescue process.

In Türkiye, post-earthquake damage assessments are primarily conducted based on external and, if necessary, internal evaluations according to ATC-20 assessment criteria (ATCouncil, 2005; Özerol Özman et al., 2024). While this method is effective for long-term structural damage assessment, its impact during the immediate response phase is limited (Lozano et al., 2023). Traditional post-disaster assessments rely heavily on visual inspections by trained field teams, leading to inefficiencies, prolonged assessment timelines, and risks to personnel due to hazardous materials and debris exposure (Braik & Koliou, 2024; Korkmaz, 2009). However, advanced technologies such as remote sensing, artificial intelligence (AI), and data analytics hold the potential to revolutionize damage assessment processes (Braik & Koliou, 2024). In this context, Kaplan and Kaplan (2021) demonstrated that structural damage estimation supported by remote sensing data could reduce the number of buildings requiring expert inspection by approximately 50% after the 2020 Samos earthquake. Detecting and mapping the adverse effects of a disaster using traditional methods is quite challenging (Mahabir et al., 2018). Compared to conventional methods, GIS and remote sensing significantly reduce the time required for such assessments (Arikan İspir & Yildiz, 2025). In their study, Braik and Koliou (2024) utilized deep learning methods for the detection and analysis of damaged buildings, producing highly accurate maps. In many studies, an accuracy rate of 70% is considered successful (Arikan İspir & Yildiz, 2025; Atik, 2023; Pan et al., 2020). Similar results were obtained in this study, where post-earthquake satellite imagery identified collapsed buildings with 71% accuracy.

While the research provides promising results for large-scale damage mapping, there is still room for improvement in terms of image quality and analysis duration. Despite the high resolution of the Göktürk satellite image used in the study, the analysis was limited to identifying only collapsed buildings, restricting the scope of general damage assessment.

Conclusion

The earthquakes on February 6, 2023, which caused massive destruction in densely populated 11 urban areas, have highlighted the need for GIS-based analysis. GIS plays key role not only in numerous fields but also in identifying areas suitable for settlement and regions with high damage risk by considering the influence and interaction of geographical factors (Sönmez, 2011). With advancements in GIS and remote sensing technologies and the emergence of innovative approaches in AI-supported analytical methods, disaster research has also significantly benefited. For disasters such as earthquakes, industrial accidents, and fires, determining the affected areas immediately after the event is critical. For this reason, GIS, remote sensing and deep learning methods that enable holistic evaluation of the disaster area after disasters that cause great destruction such as earthquakes can offer effective solutions.

After disasters, the primary and most crucial data sources are existing geographic datasets and remote sensing imagery. These datasets can be used to identify affected areas and perform earthquake impact analyses based on the images. UAVs and drones play a significant role in this process (Maraş & Sarıyıldız, 2023). In this study, similar images were used to detect and map destroyed buildings after the earthquake. ArcGIS Pro 3.4.0 software was utilized for the detection of collapsed buildings using post-disaster remotely sensed imagery with deep learning-based Mask R-CNN architecture. To validate the method used, a building damage detection dataset was created using GÖKTÜRK satellite images obtained three days after the February 6, 2023, Kahramanmaraş earthquake, pre-earthquake orthophotos from 2020, and geographic vector data. Subsequently, the dataset of collapsed and intact buildings was trained and validated using the Mask R-CNN architecture in the ArcGIS Pro deep learning tool "Train Deep Learning Model." The analysis results demonstrated that the Mask R-CNN model, combined with the ResNet-50 backbone and trained with two different batch sizes for 20 epochs, produced results close to accuracy.

The key contributions of this study are (i) the rapid damage assessment based on GIS and RS datasets after a disaster and (ii) providing information that can help identify priority areas for search and rescue efforts and accelerate early intervention processes. As a result, the study has proven that GIS and deep learning models can facilitate the initial detection and mapping of earthquake-induced damage, supporting decision-makers effectively.

Declarations

Author Contribution Statement

All data collection, analysis and text writing of the study were carried out by the author.

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